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Dane et al.

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(54) **SYSTEMS AND METHODS FOR NON-OBSTACLE AREA DETECTION**

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Related U.S. Application Data

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(51) **Int. Cl.**

G06K 9/00 (2006.01)
G06T 7/20 (2017.01)

(Continued)

(52) **U.S. Cl.**

CPC ***G06T 7/20*** (2013.01); ***G06K 9/00791*** (2013.01); ***G06K 9/00798*** (2013.01); ***G06T 7/11*** (2017.01);

(Continued)

(58) **Field of Classification Search**

None

See application file for complete search history.

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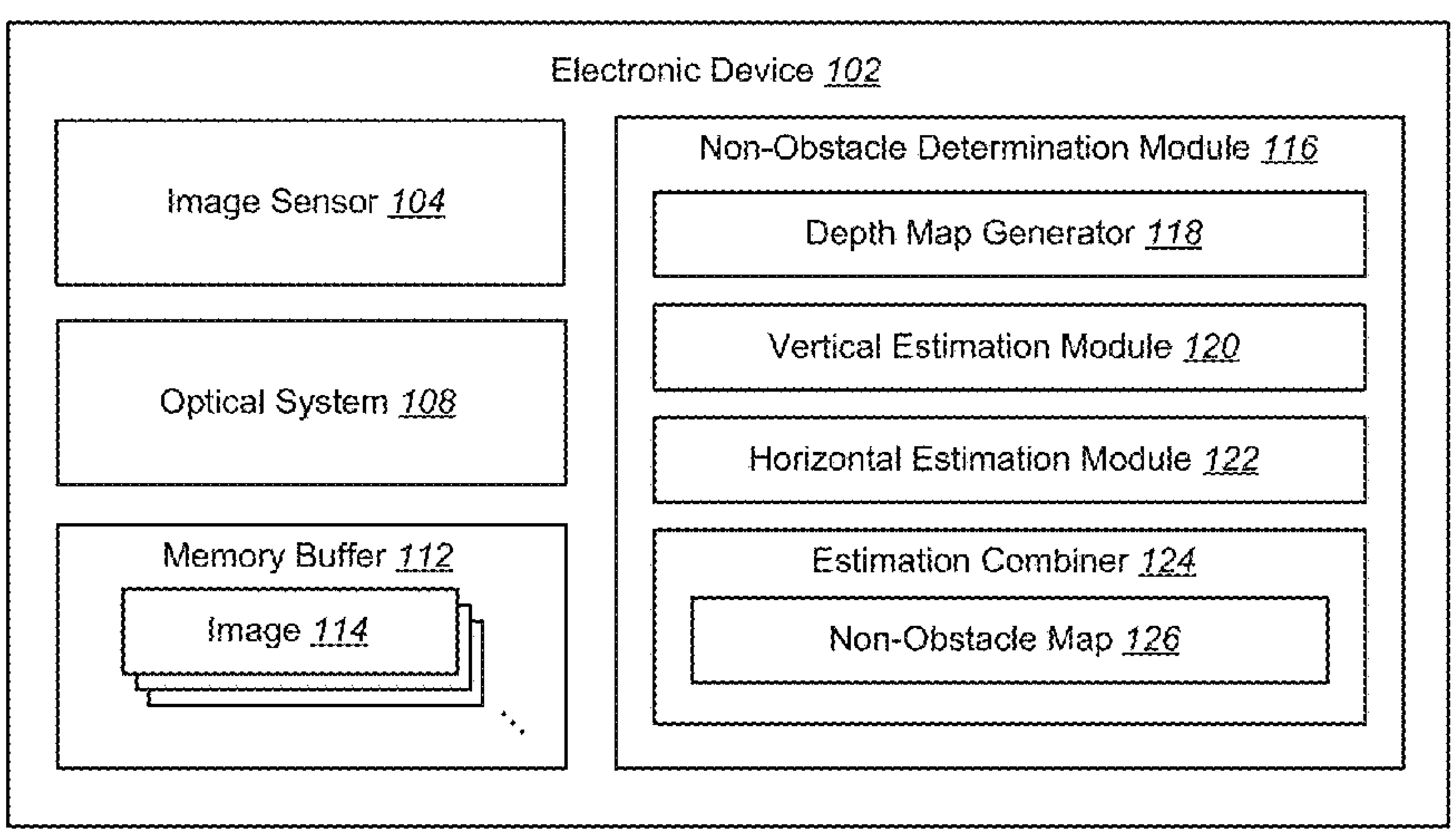
Primary Examiner — Andrae A Allison
(74) *Attorney, Agent, or Firm* — Austin Rapp

(57) **ABSTRACT**

A method performed by an electronic device is described. The method includes generating a depth map of a scene external to a vehicle. The method also includes performing first processing in a first direction of a depth map to determine a first non-obstacle estimation of the scene. The method also includes performing second processing in a second direction of the depth map to determine a second non-obstacle estimation of the scene. The method further includes combining the first non-obstacle estimation and the second non-obstacle estimation to determine a non-obstacle map of the scene. The combining includes combining comprises selectively using a first reliability map of the first processing and/or a second reliability map of the second processing The method additionally includes navigating the vehicle using the non-obstacle map.

30 Claims, 17 Drawing Sheets



(51) **Int. Cl.**

G06T 7/50	(2017.01)
G06T 7/507	(2017.01)
G06T 7/11	(2017.01)
G06K 9/62	(2006.01)

(52) **U.S. Cl.**

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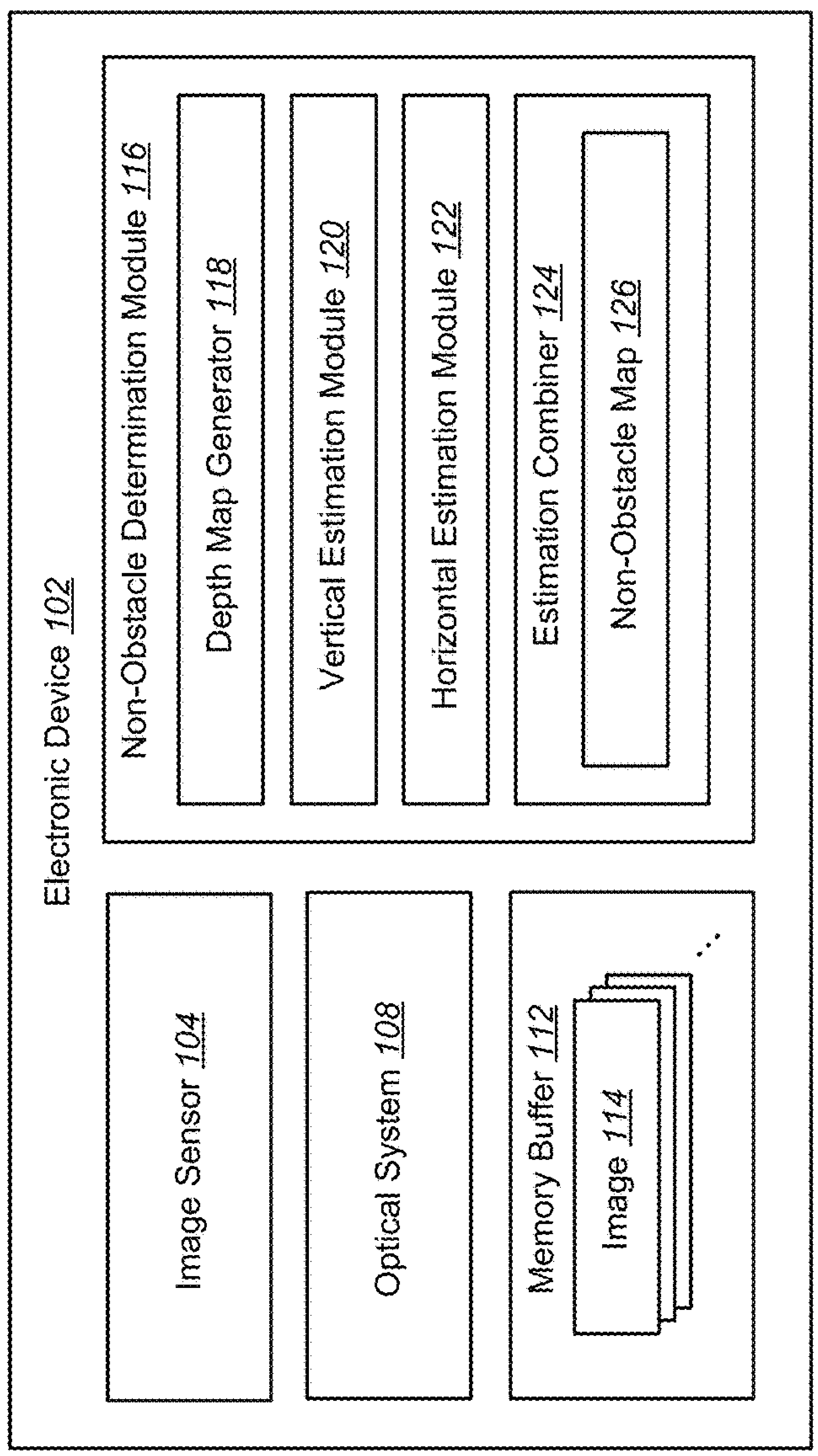

Electronic Device 102
Image Sensor 104
Optical System 108
Memory Buffer 112
Image 114
...
Non-Obstacle Determination Module 116
Depth Map Generator 118
Vertical Estimation Module 120
Horizontal Estimation Module 122
Estimation Combiner 124
Non-Obstacle Map 126

FIG. 1

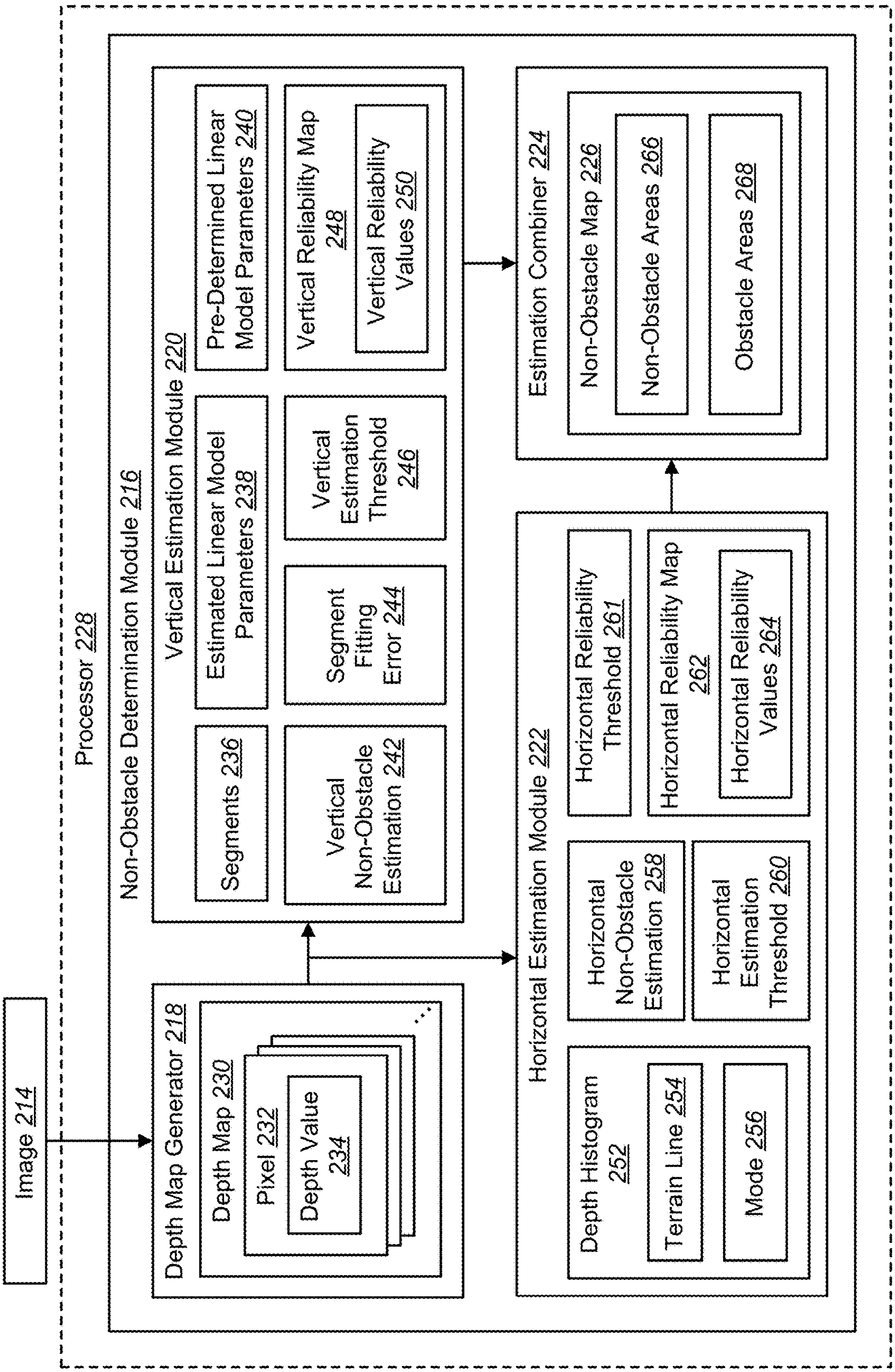


Image 214
Processor 228
Non-Obstacle Determination Module 216
Depth Map Generator 218
Depth Map 230
Pixel 232
Depth Value 234
Vertical Estimation Module 220
Segments 236
Estimated Linear Model Parameters 238
Pre-Determined Linear Model Parameters 240
Vertical Non-Obstacle Estimation 242
Segment Fitting Error 244
Vertical Estimation Threshold 246
Vertical Reliability Map 248
Vertical Reliability Values 250
Horizontal Estimation Module 222
Depth Histogram 252
Terrain Line 254
Mode 256
Horizontal Non-Obstacle Estimation 258
Horizontal Estimation Threshold 260
Horizontal Reliability Threshold 261
Horizontal Reliability Map 262
Horizontal Reliability Values 264
Estimation Combiner 224
Non-Obstacle Map 226
Non-Obstacle Areas 266
Obstacle Areas 268

FIG. 2

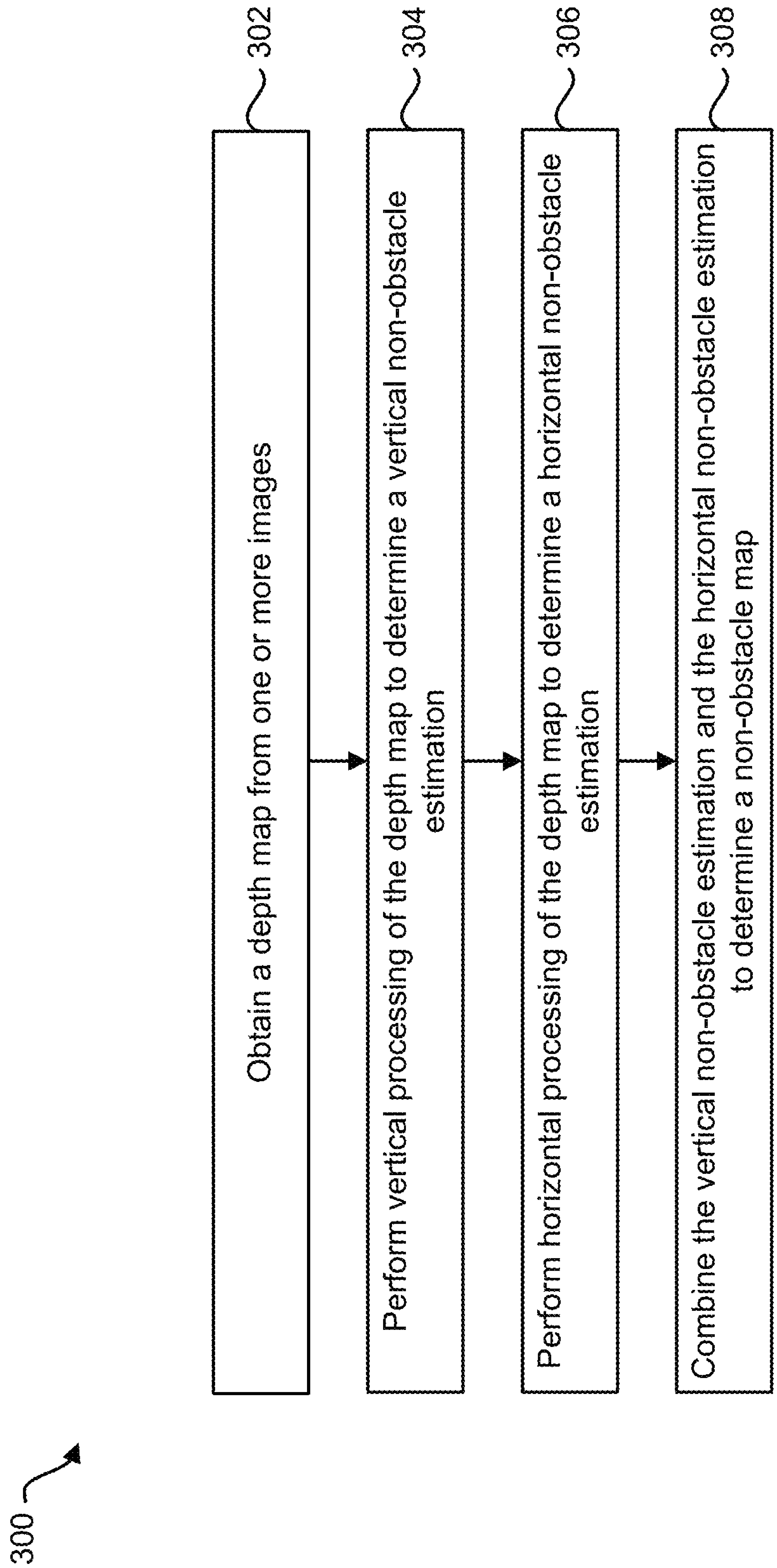

300
302
Obtain a depth map from one or more images
304
Perform vertical processing of the depth map to determine a vertical non-obstacle estimation
306
Perform horizontal processing of the depth map to determine a horizontal non-obstacle estimation
308
Combine the vertical non-obstacle estimation and the horizontal non-obstacle estimation to determine a non-obstacle map

FIG. 3

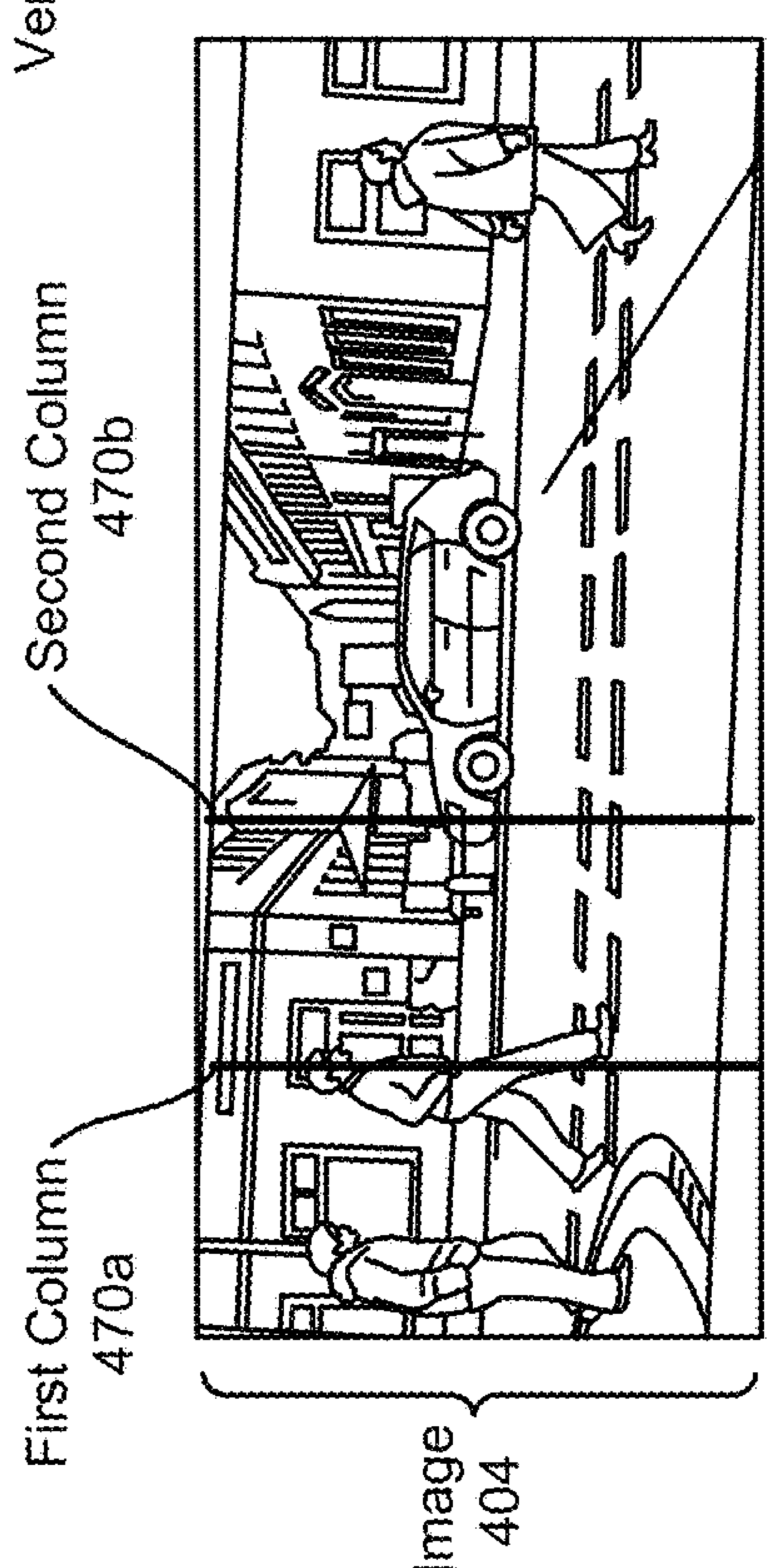


FIG. 4A

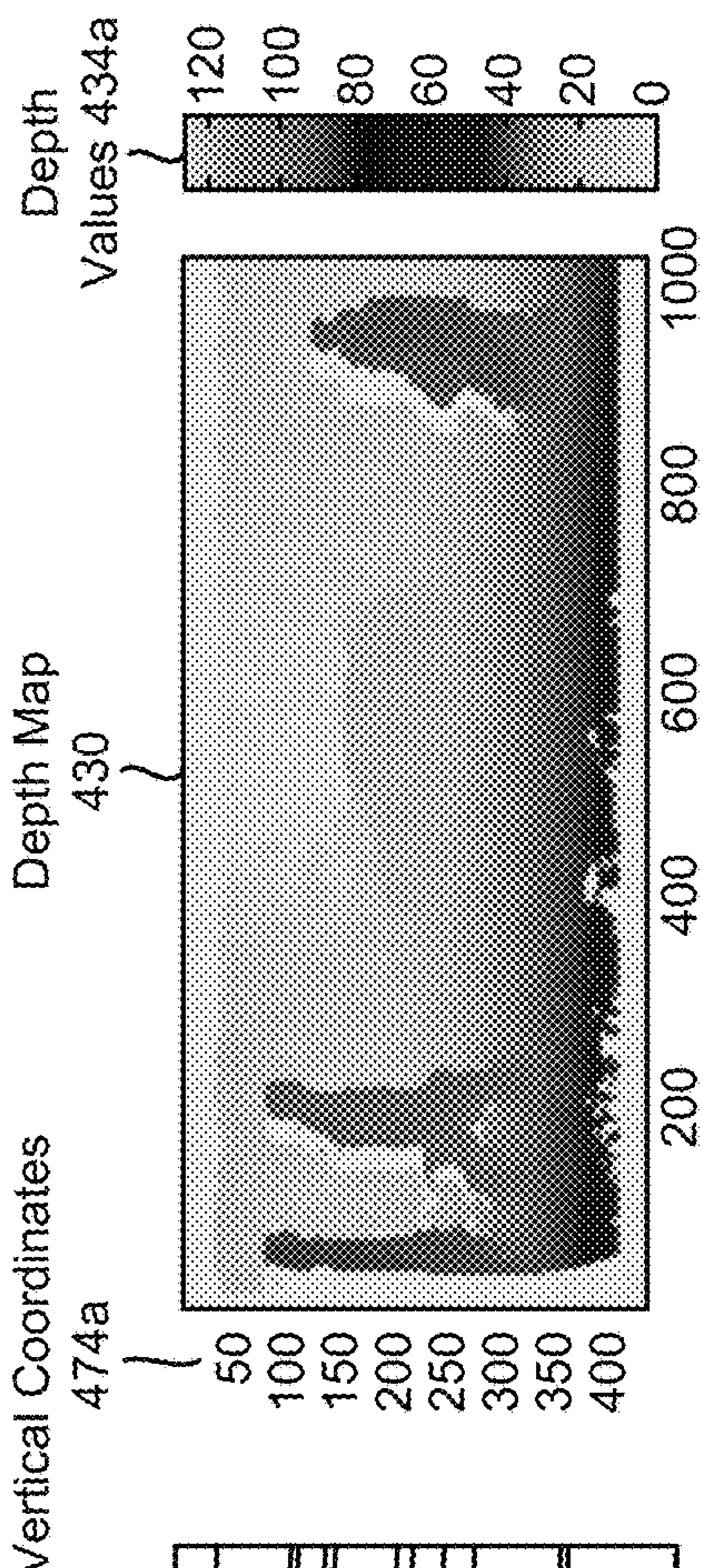


FIG. 4B

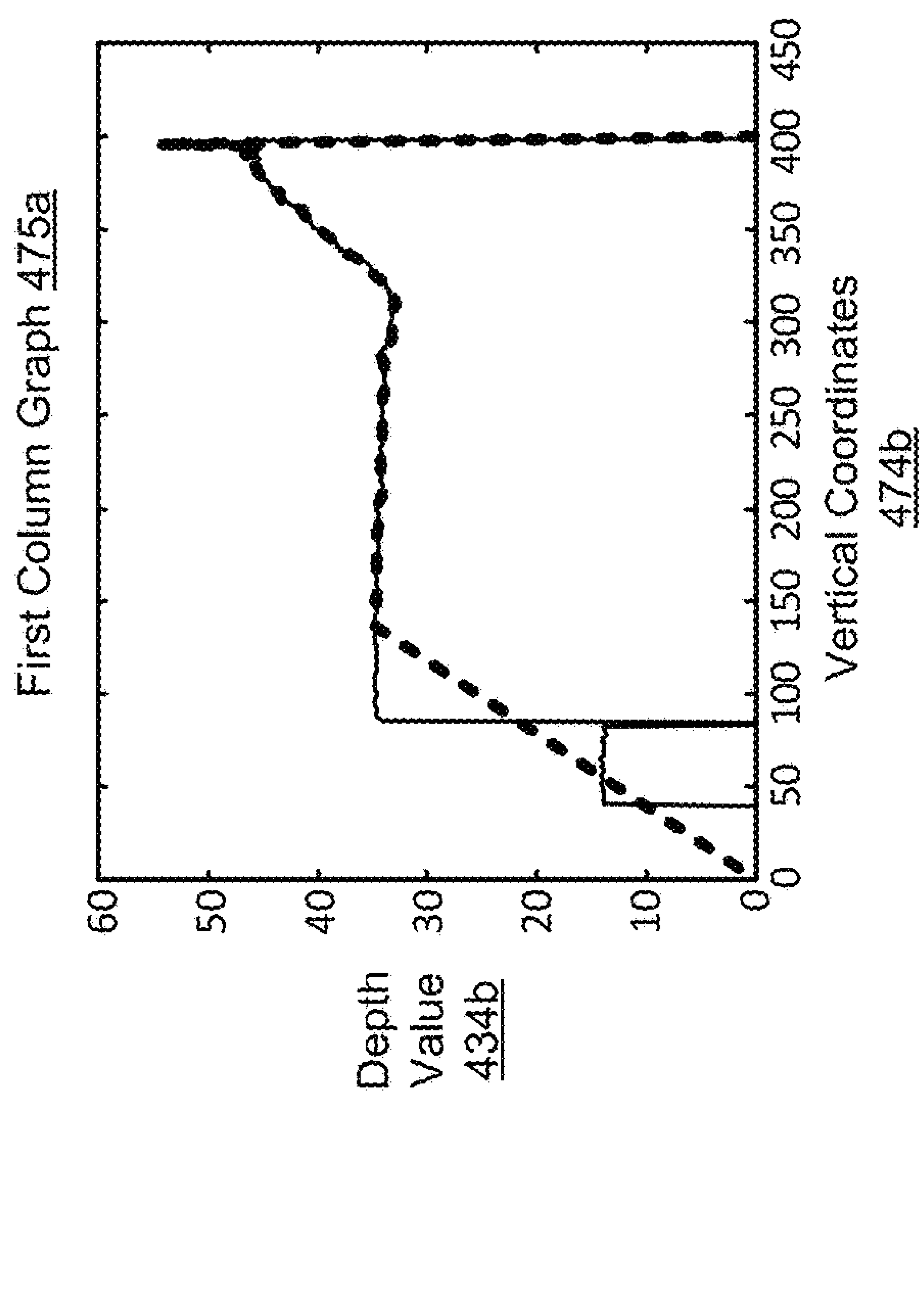


FIG. 4C

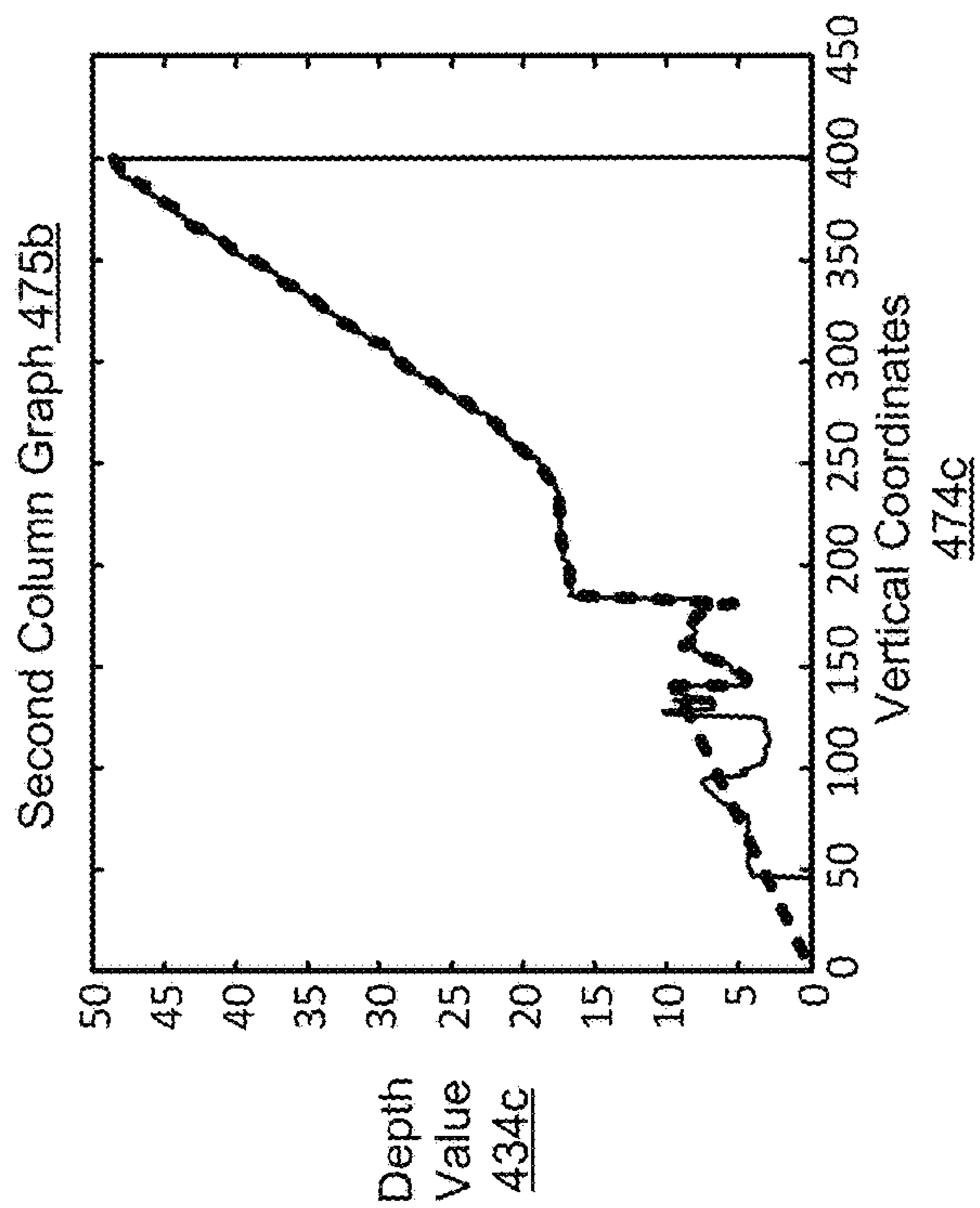


FIG. 4D

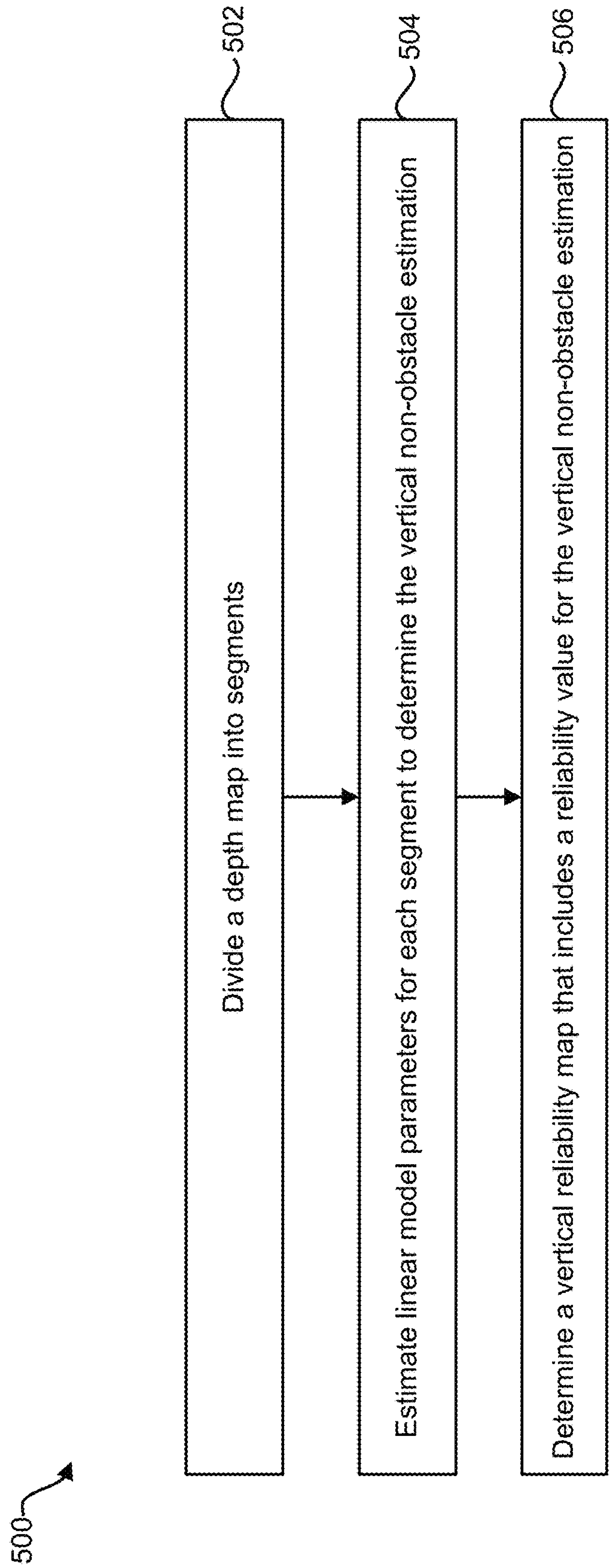

500
502
Divide a depth map into segments
504
Estimate linear model parameters for each segment to determine the vertical non-obstacle estimation
506
Determine a vertical reliability map that includes a reliability value for the vertical non-obstacle estimation

FIG. 5

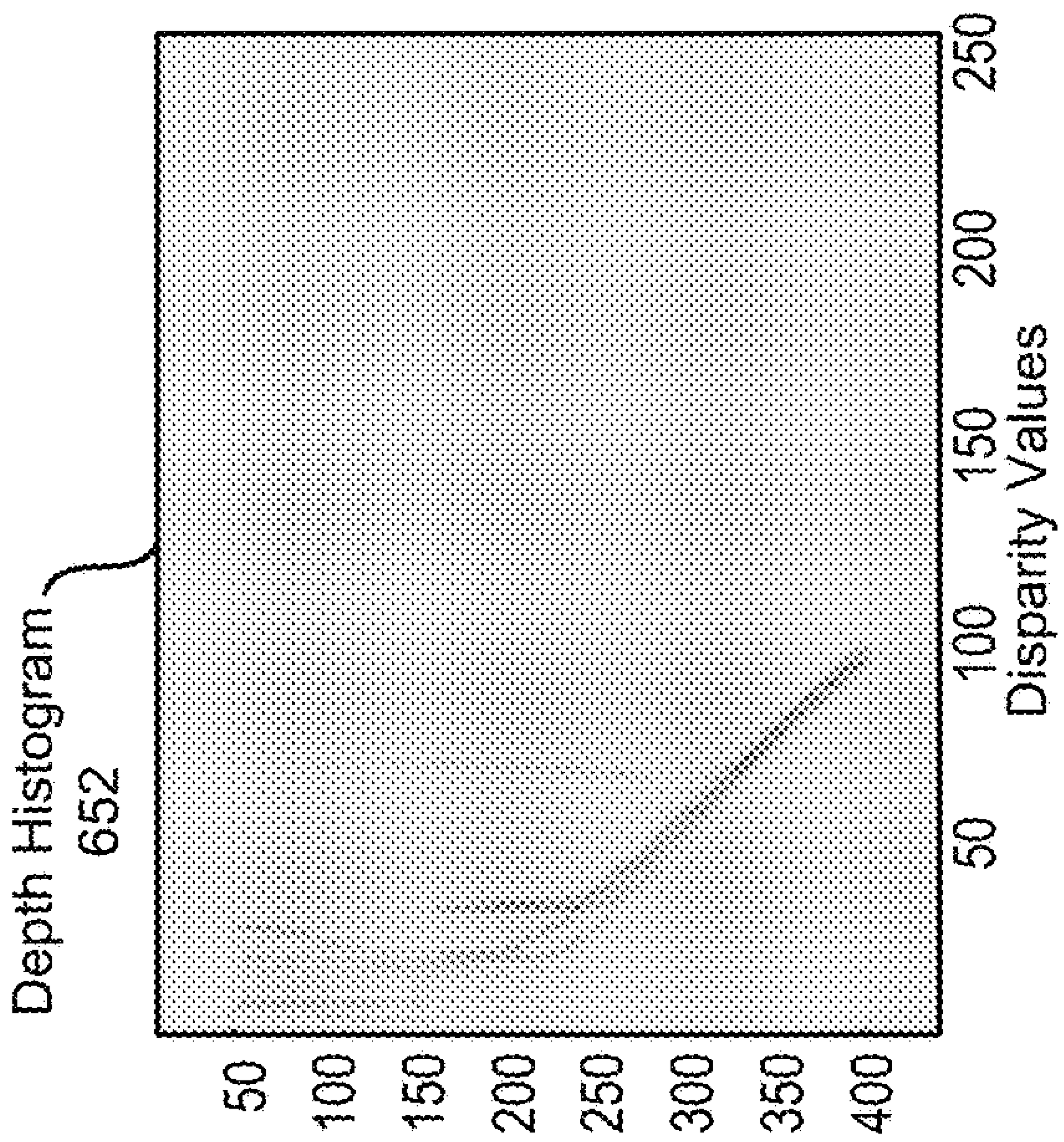


FIG. 6B

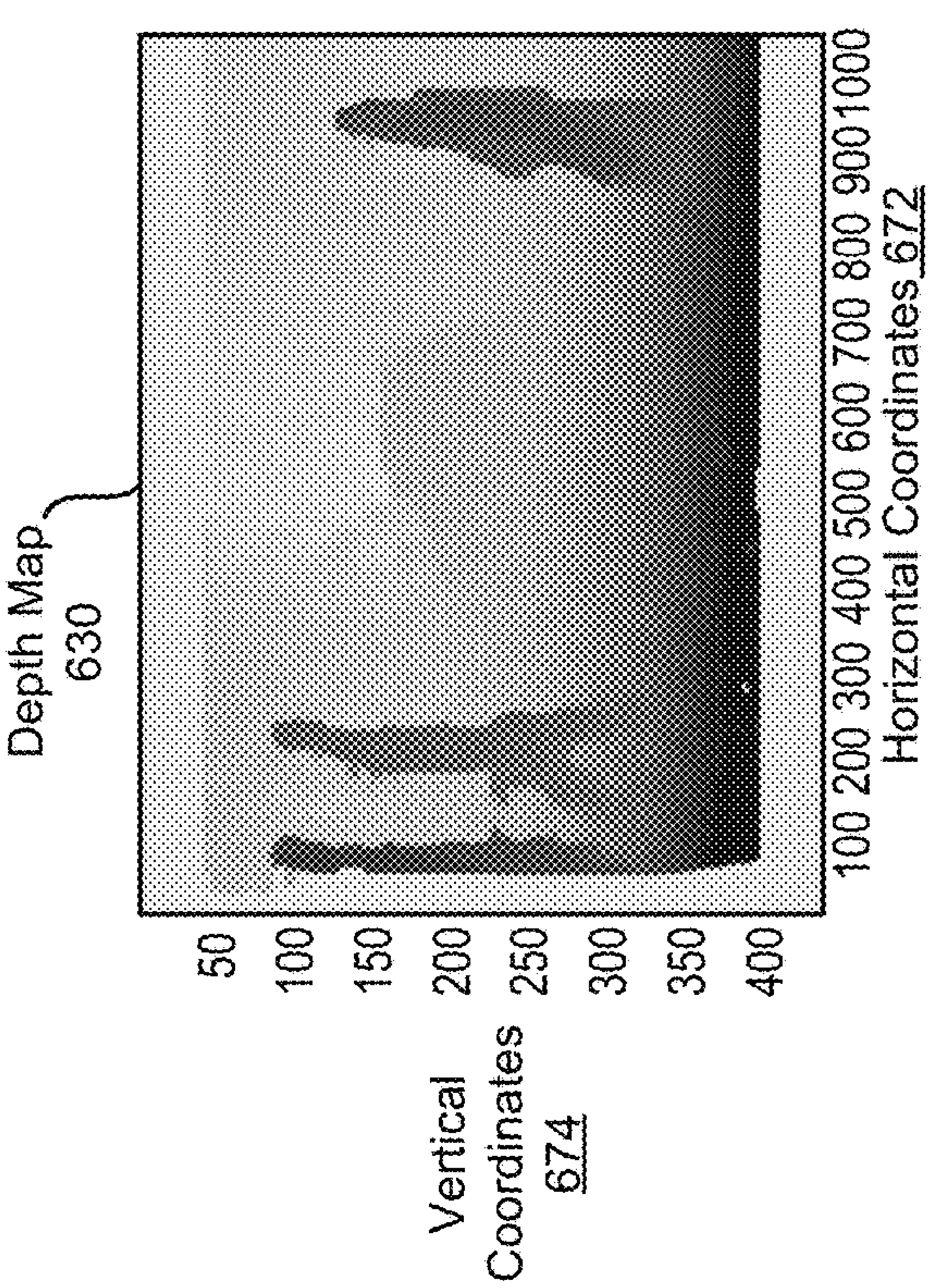


FIG. 6A

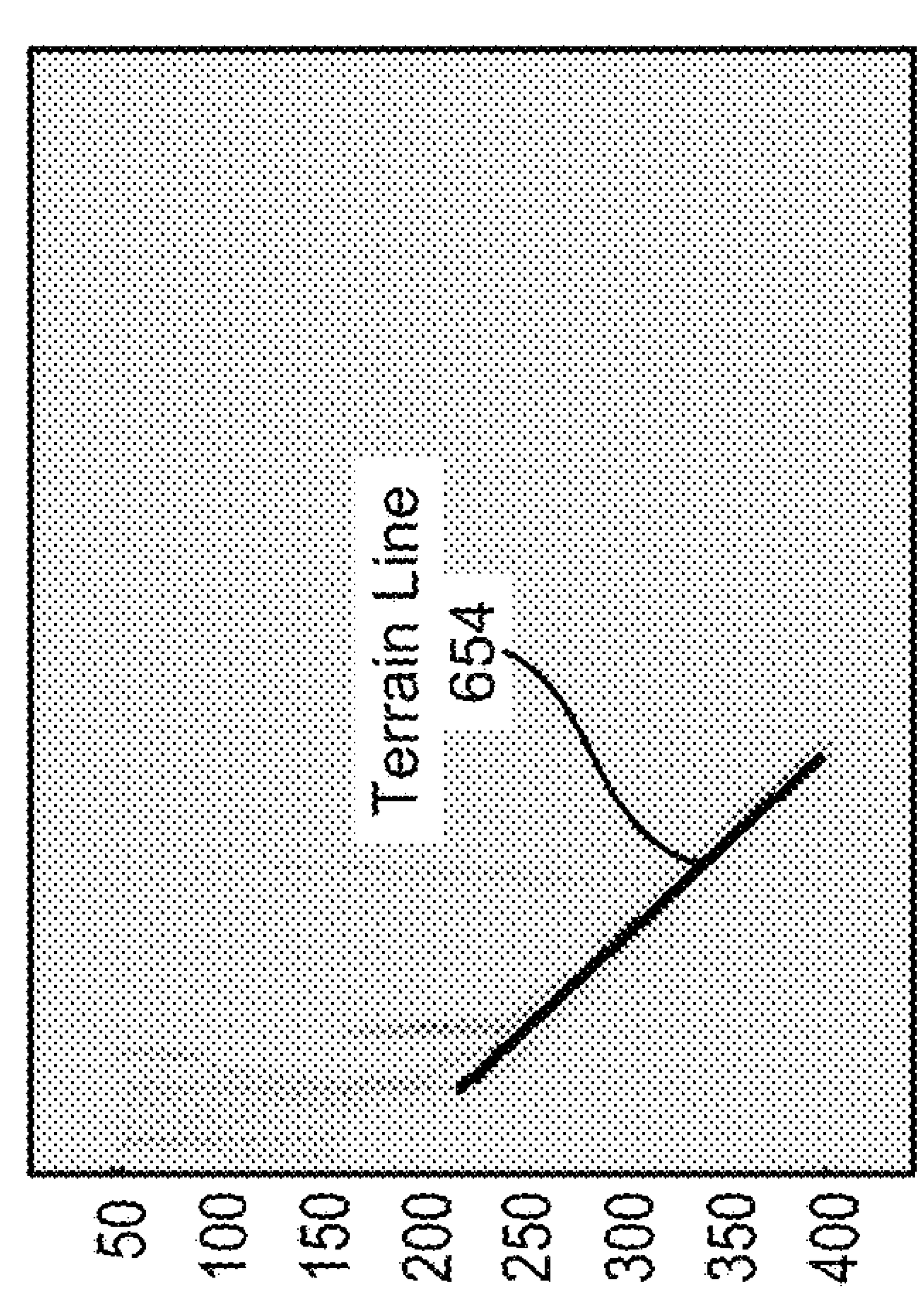


FIG. 6D

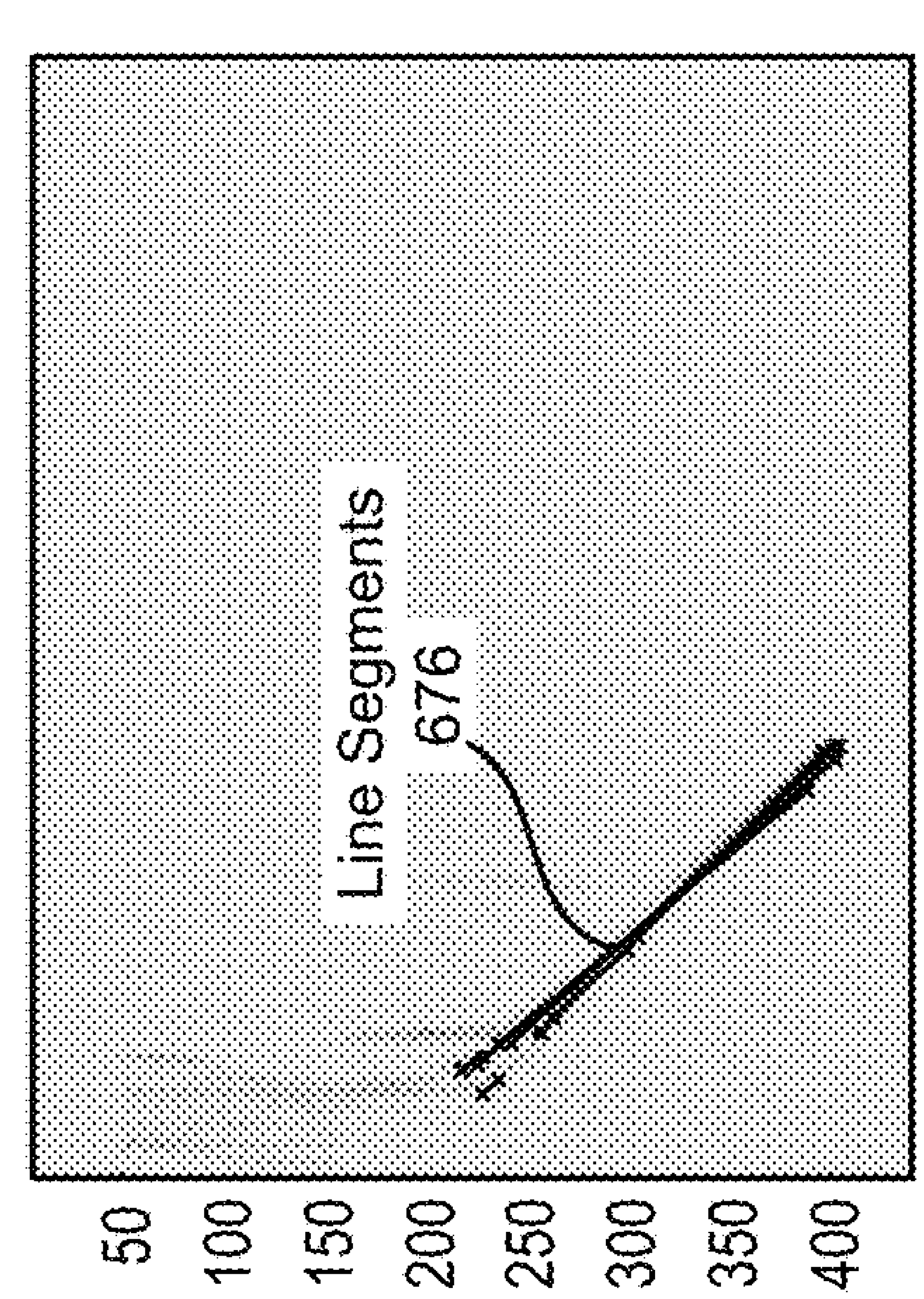


FIG. 6C

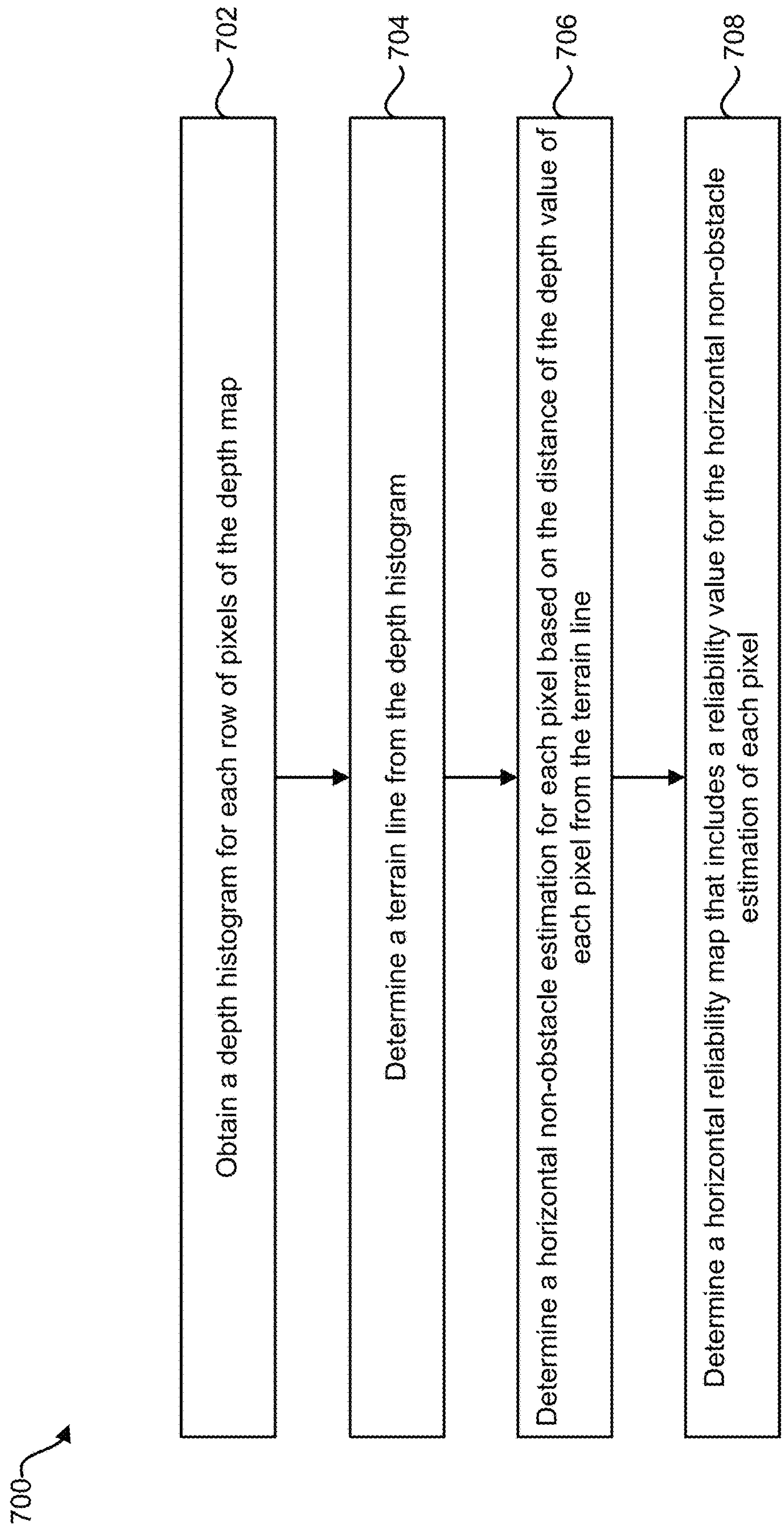

700
702
Obtain a depth histogram for each row of pixels of the depth map
704
Determine a terrain line from the depth histogram
706
Determine a horizontal non-obstacle estimation for each pixel based on the distance of the depth value of each pixel from the terrain line
708
Determine a horizontal reliability map that includes a reliability value for the horizontal non-obstacle estimation of each pixel

FIG. 7

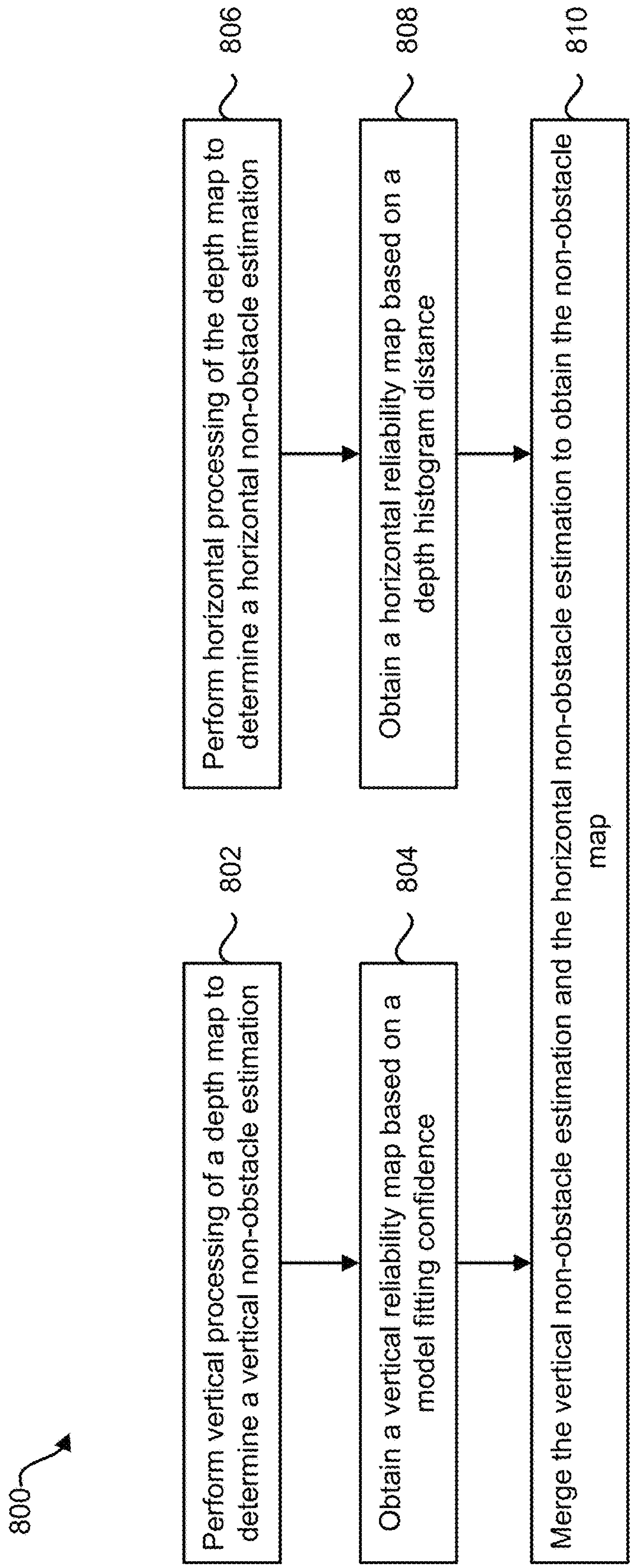

800
Perform vertical processing of a depth map to determine a vertical non-obstacle estimation
802
Obtain a vertical reliability map based on a model fitting confidence
804
Perform horizontal processing of the depth map to determine a horizontal non-obstacle estimation
806
Obtain a horizontal reliability map based on a depth histogram distance
808
Merge the vertical non-obstacle estimation and the horizontal non-obstacle estimation to obtain the non-obstacle map
810

FIG. 8

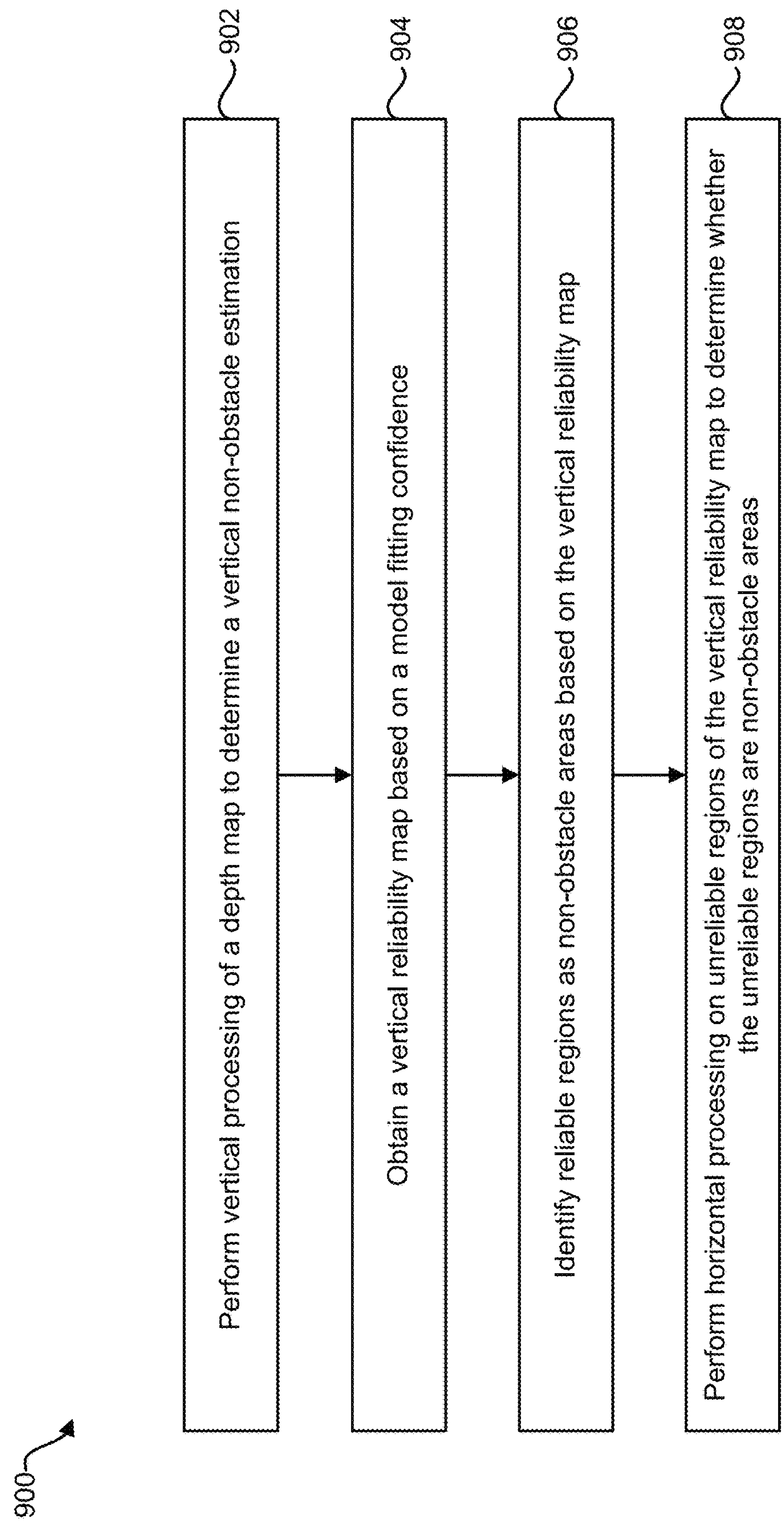

900
902
Perform vertical processing of a depth map to determine a vertical non-obstacle estimation
904
Obtain a vertical reliability map based on a model fitting confidence
906
Identify reliable regions as non-obstacle areas based on the vertical reliability map
908
Perform horizontal processing on unreliable regions of the vertical reliability map to determine whether the unreliable regions are non-obstacle areas

FIG. 9

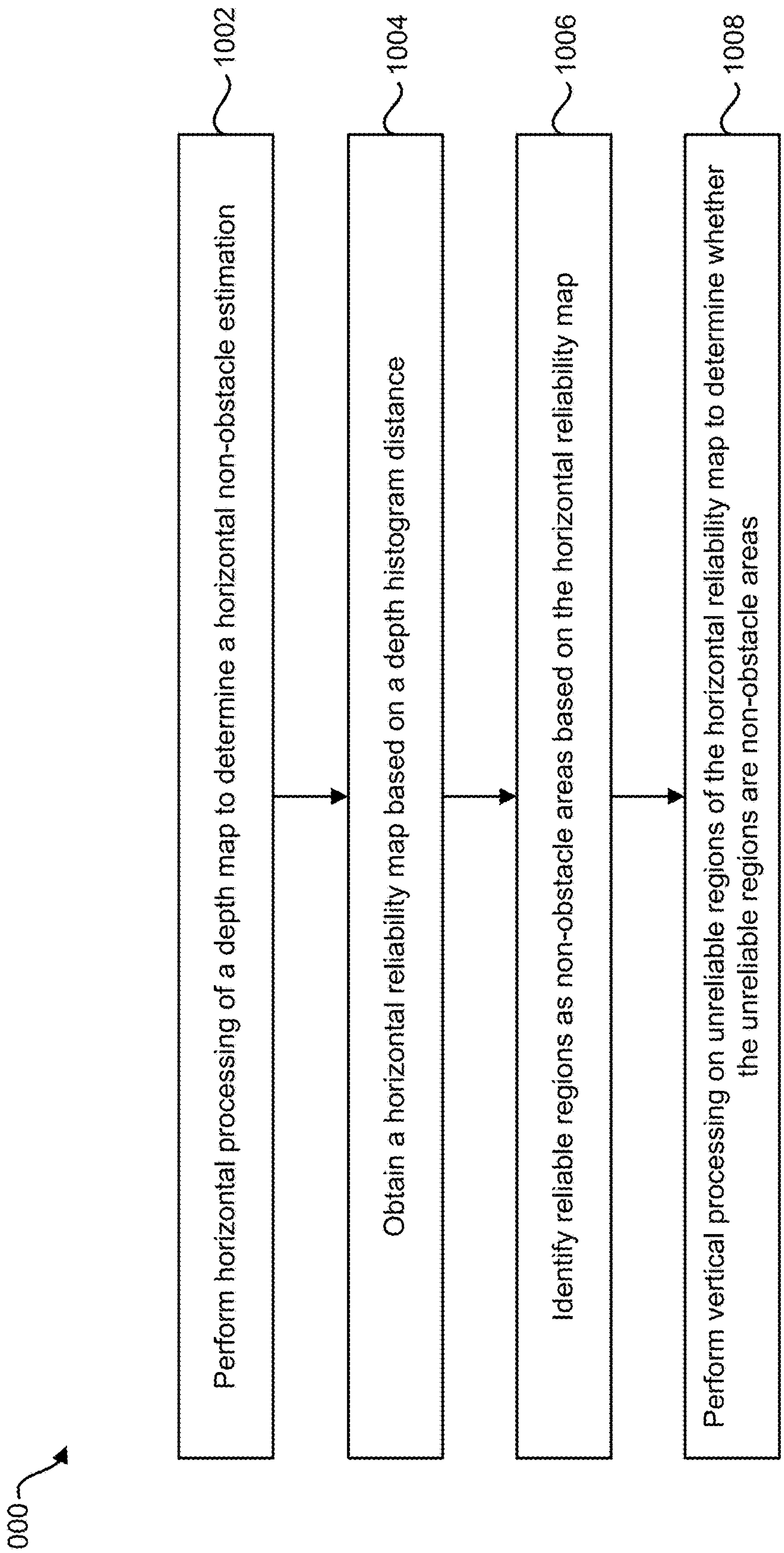

1000
1002
Perform horizontal processing of a depth map to determine a horizontal non-obstacle estimation
1004
Obtain a horizontal reliability map based on a depth histogram distance
1006
Identify reliable regions as non-obstacle areas based on the horizontal reliability map
1008
Perform vertical processing on unreliable regions of the horizontal reliability map to determine whether the unreliable regions are non-obstacle areas

FIG. 10

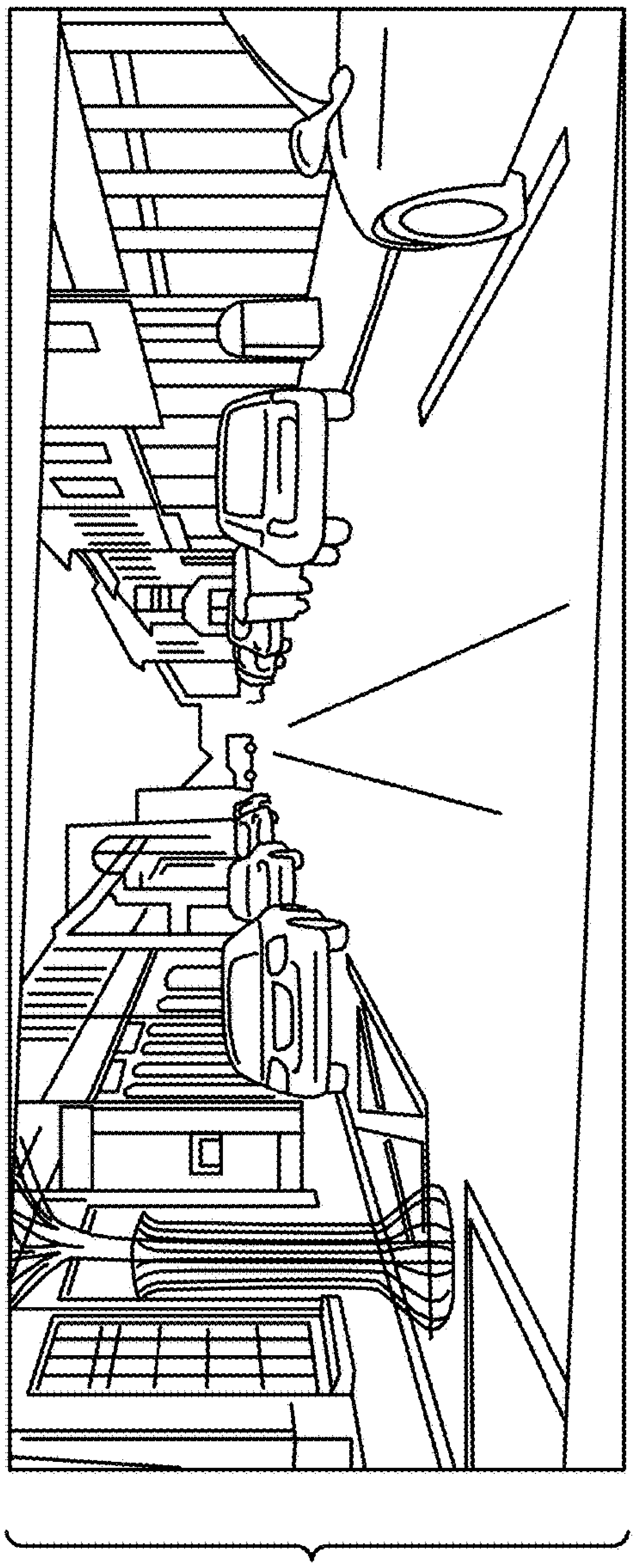


FIG. 11A

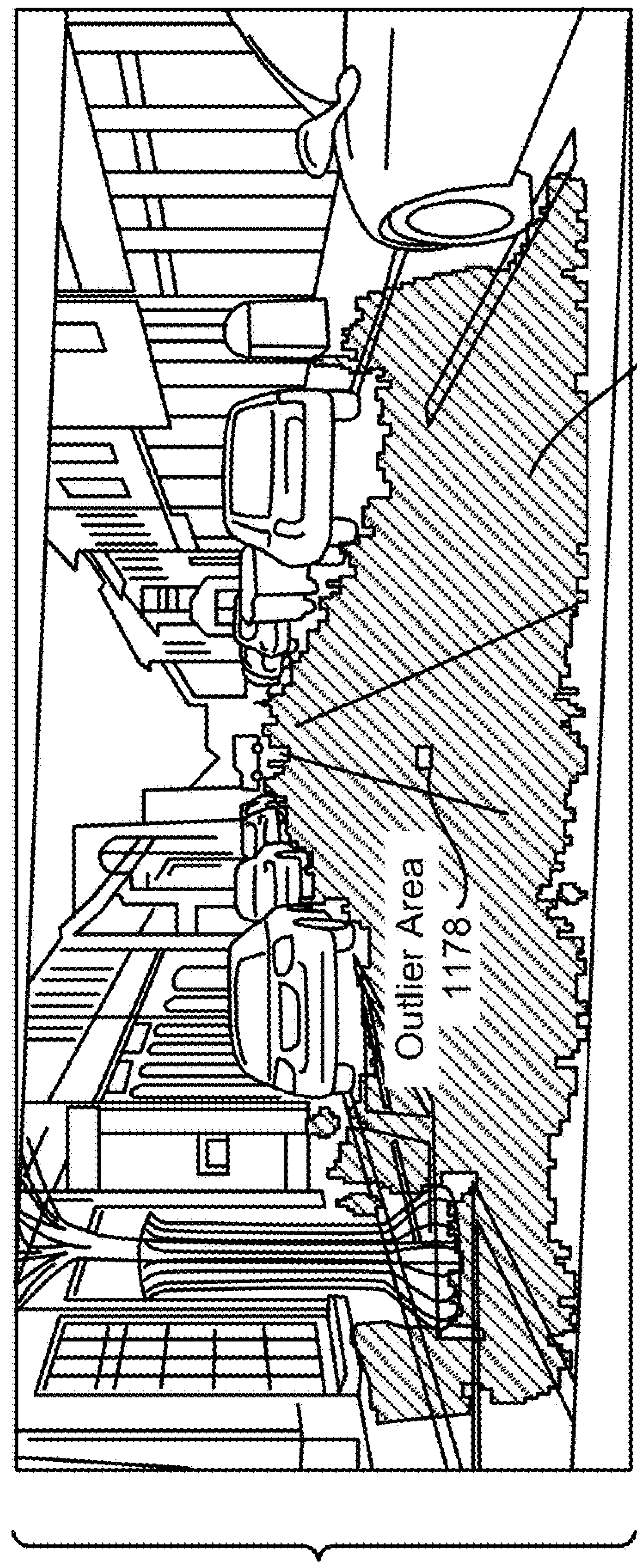
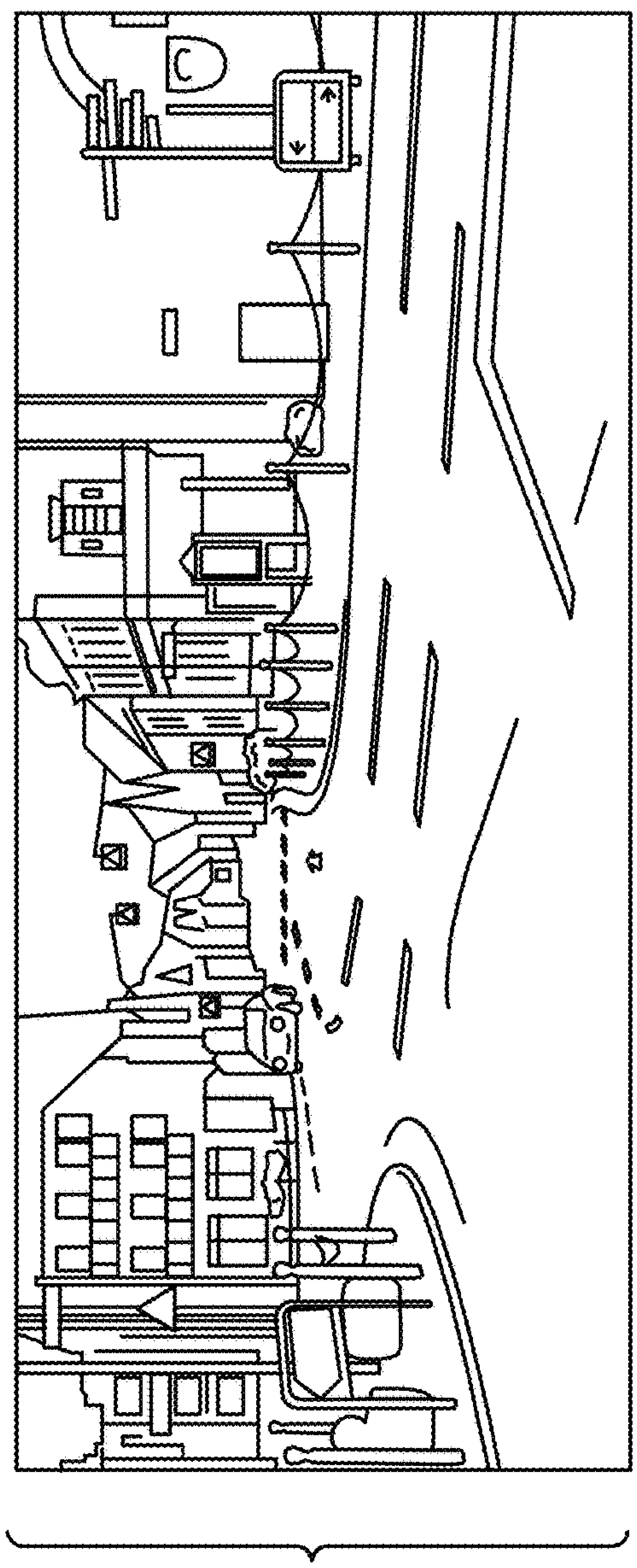
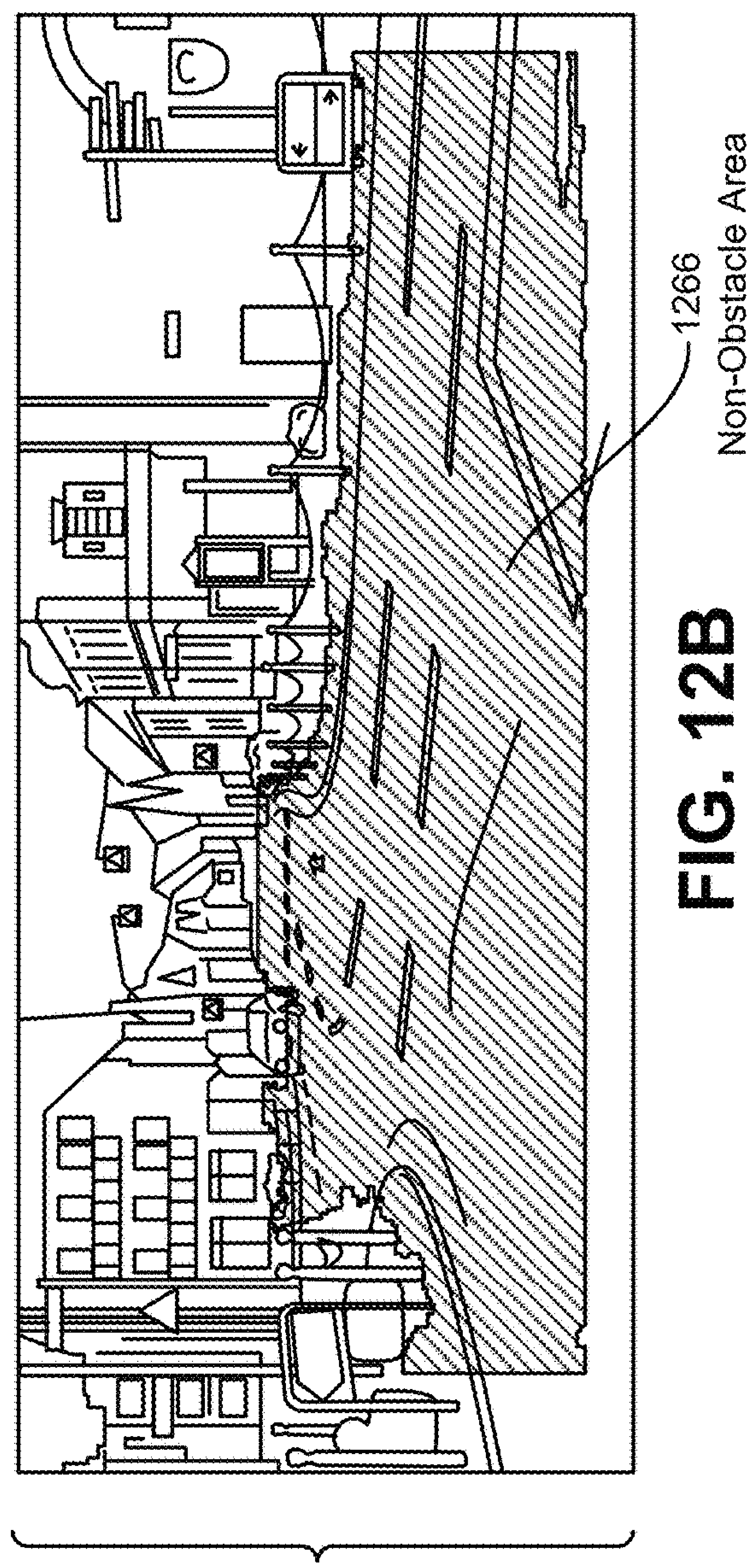


FIG. 11B



Original Image 1214a

FIG. 12A



Processed Image 1214b

FIG. 12B

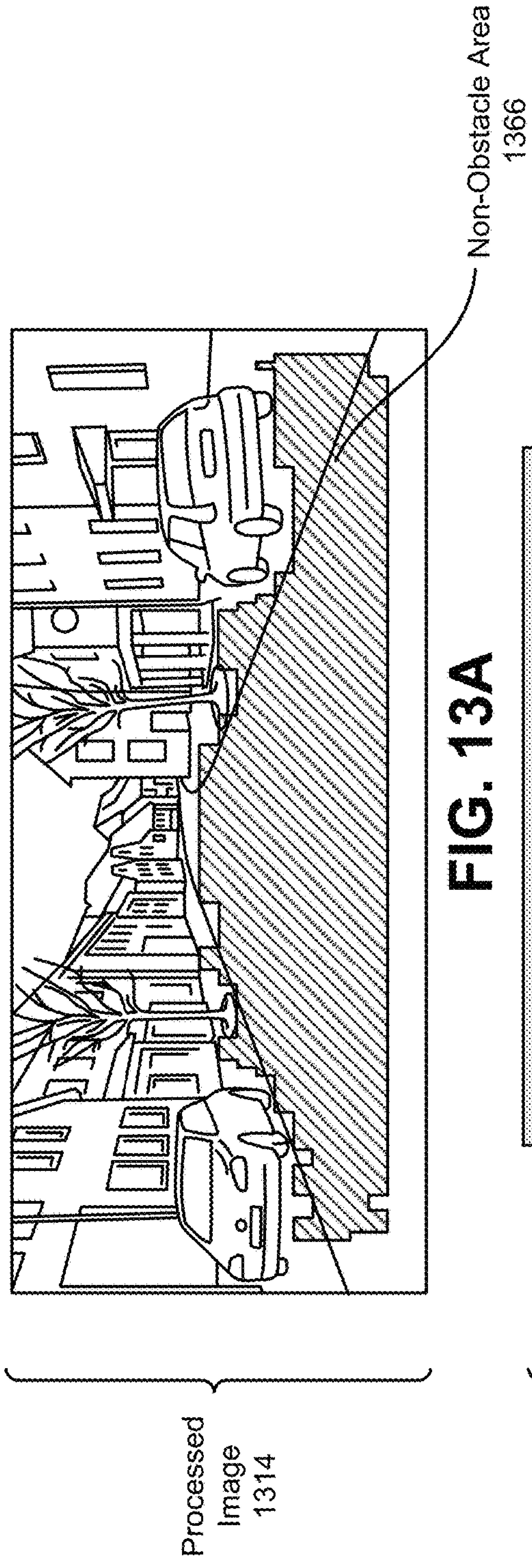


FIG. 13A

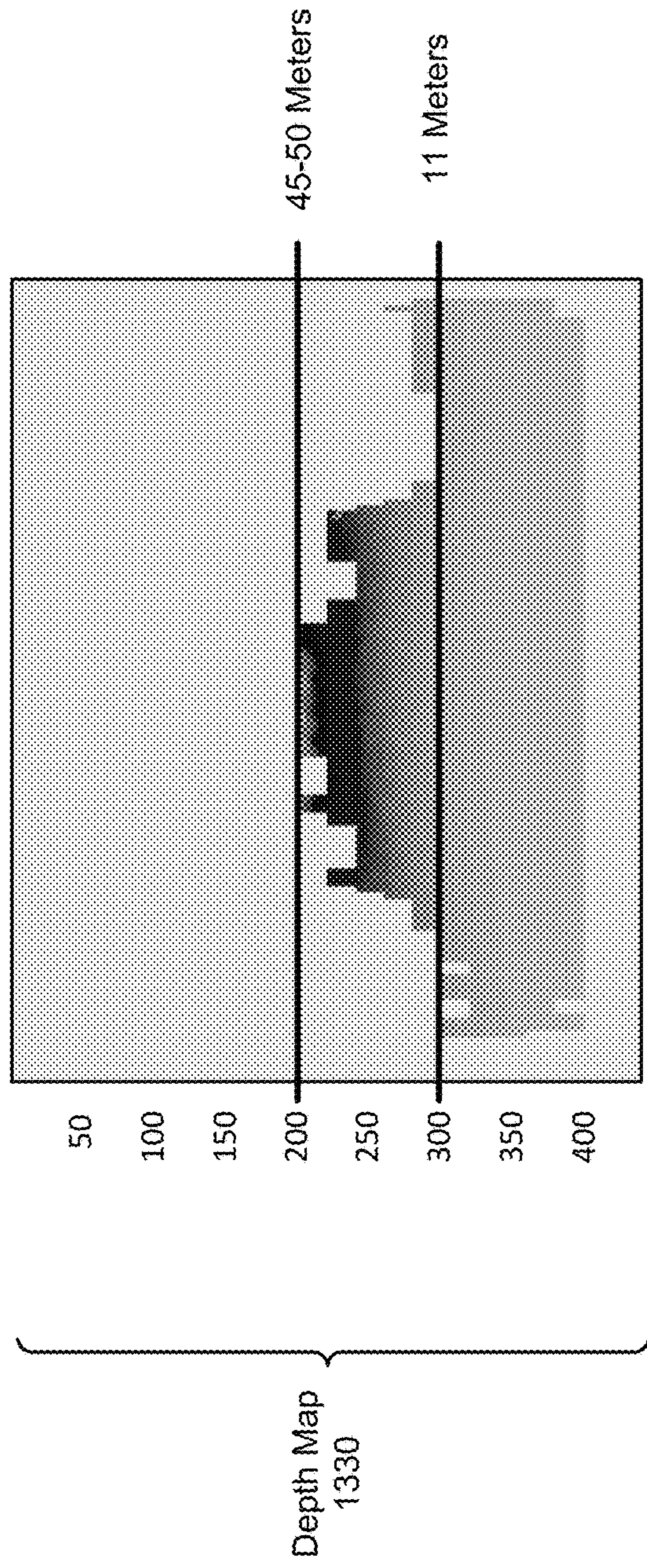
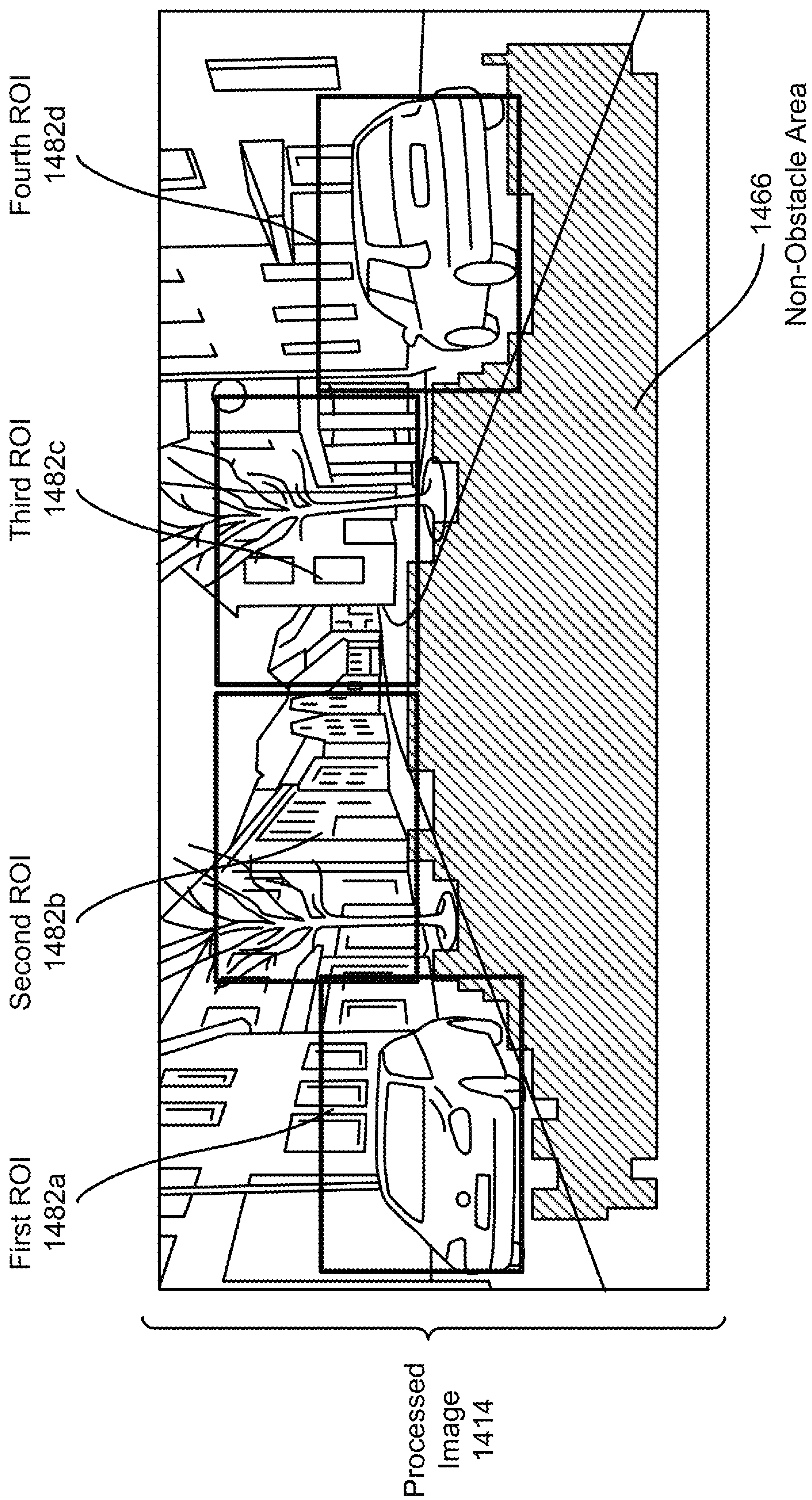


FIG. 13B



First ROI
1482a
Second ROI
1482b
Third ROI
1482c
Fourth ROI
1482d
1466
Non-Obstacle Area
Processed
Image
1414

FIG. 14

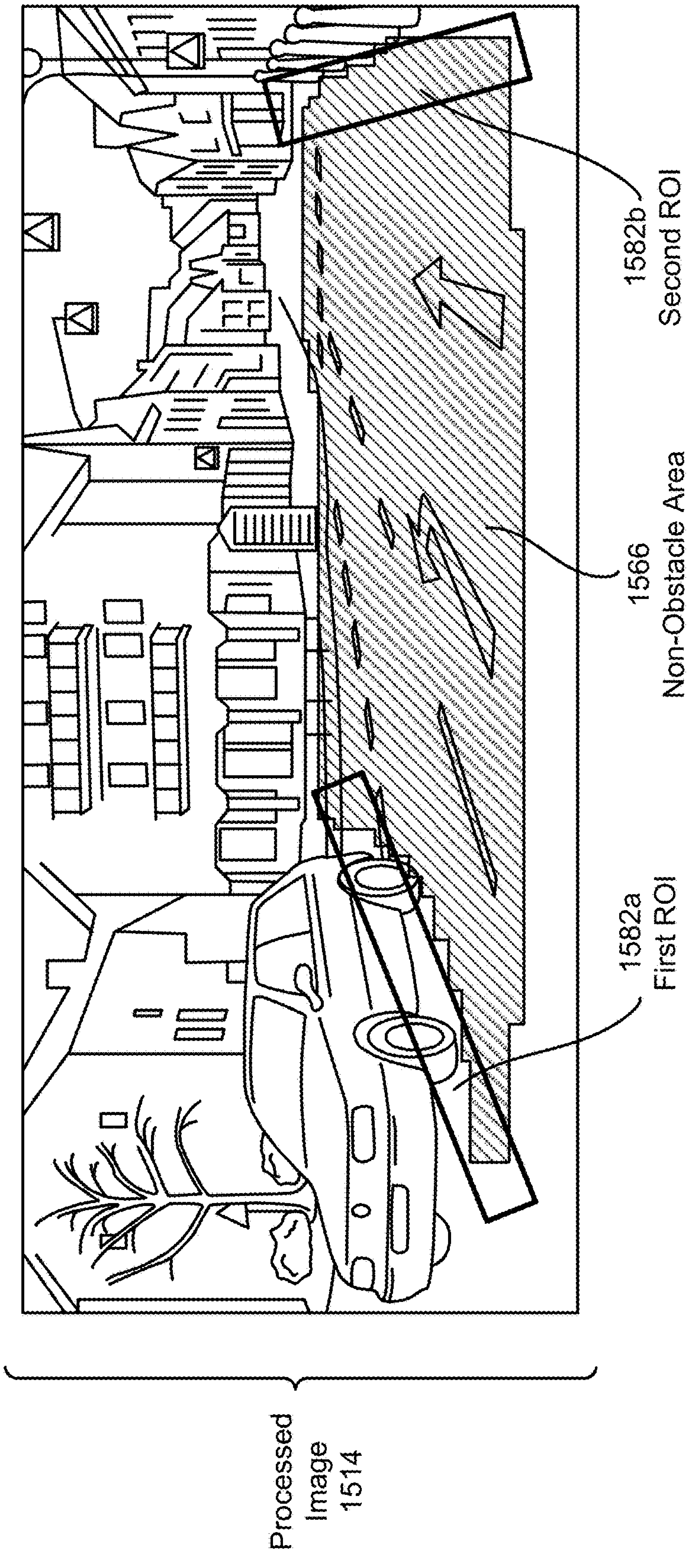

1582b
Second ROI
1566
Non-Obstacle Area
1582a
First ROI
Processed Image 1514

FIG. 15

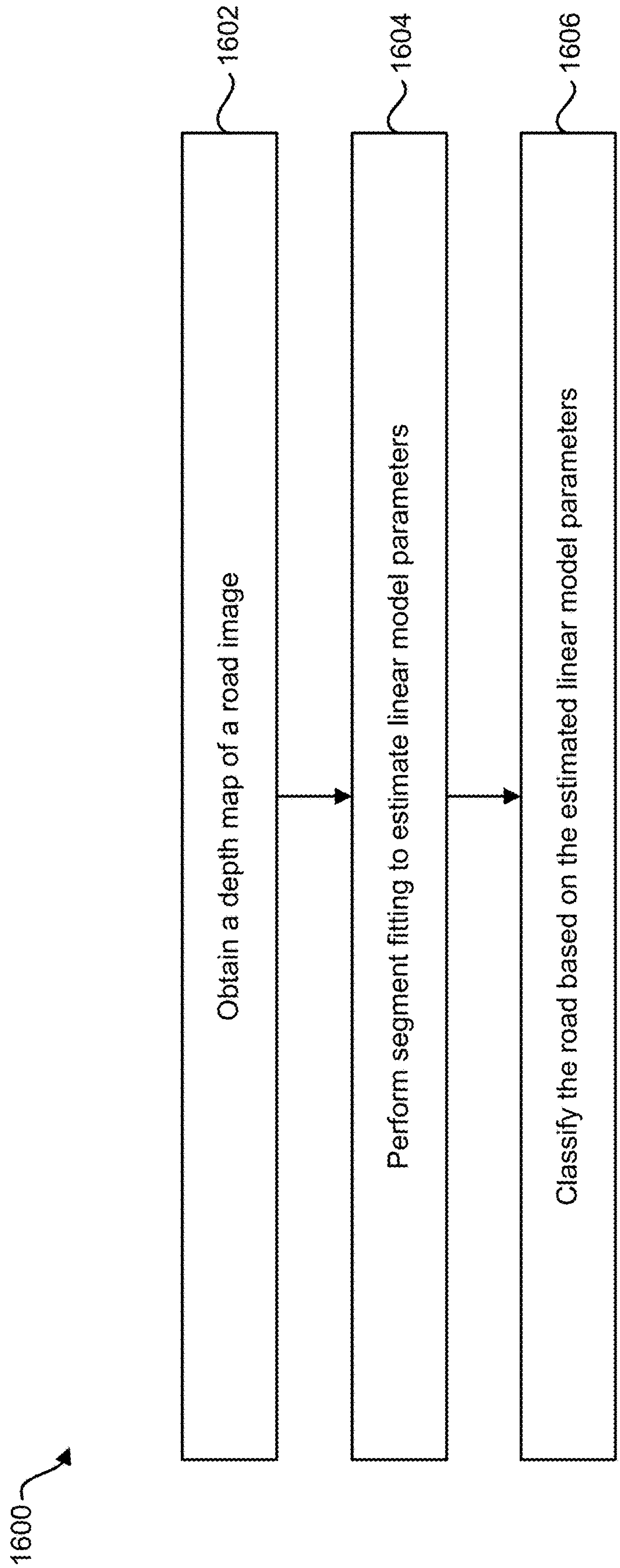

1600
1602
Obtain a depth map of a road image
1604
Perform segment fitting to estimate linear model parameters
1606
Classify the road based on the estimated linear model parameters

FIG. 16

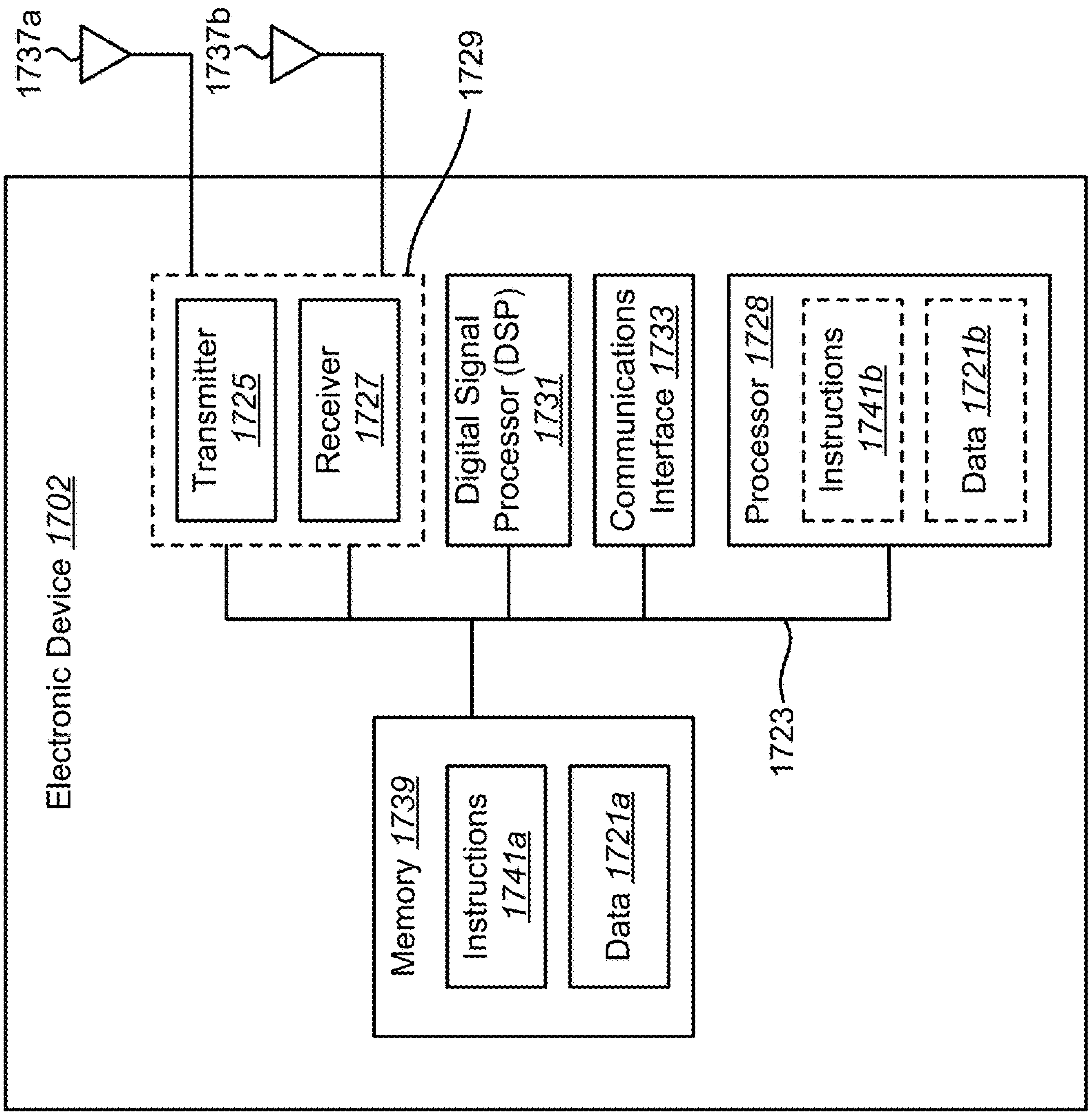

1737a
1737b
1729
Electronic Device 1702
Transmitter 1725
Receiver 1727
Digital Signal Processor (DSP) 1731
Communications Interface 1733
Processor 1728
Instructions 1741b
Data 1721b
Memory 1739
Instructions 1741a
Data 1721a
1723

FIG. 17

SYSTEMS AND METHODS FOR NON-OBSTACLE AREA DETECTION

RELATED APPLICATIONS

This application is a continuation of U.S. patent application Ser. No. 14/858,471, filed Sep. 18, 2015, for "SYSTEMS AND METHODS FOR NON-OBSTACLE AREA DETECTION," which is assigned to the assignee hereof and hereby expressly incorporated by reference herein.

FIELD OF DISCLOSURE

The present disclosure relates generally to electronic devices. More specifically, the present disclosure relates to systems and methods for non-obstacle area detection.

BACKGROUND

In the last several decades, the use of electronic devices has become common. In particular, advances in electronic technology have reduced the cost of increasingly complex and useful electronic devices. Cost reduction and consumer demand have proliferated the use of electronic devices such that they are practically ubiquitous in modern society. As the use of electronic devices has expanded, so has the demand for new and improved features of electronic devices. More specifically, electronic devices that perform new functions and/or that perform functions faster, more efficiently or with higher quality are often sought after.

Some electronic devices (e.g., cameras, video camcorders, digital cameras, cellular phones, smart phones, computers, televisions, etc.) capture and/or utilize images. For example, a smartphone may capture and/or process still and/or video images. In automotive and autonomous vehicle applications, obstacle detection may be performed by processing an image. Processing images may demand a relatively large amount of time, memory and energy resources. The resources demanded may vary in accordance with the complexity of the processing.

It may be difficult to implement some complex processing tasks. For example, some platforms may have limited processing, memory and/or energy resources. Furthermore, some applications may be time sensitive. As can be observed from this discussion, systems and methods that improve image processing may be beneficial.

SUMMARY

A method performed by an electronic device is described. The method includes performing vertical processing of a depth map to determine a vertical non-obstacle estimation. The method also includes performing horizontal processing of the depth map to determine a horizontal non-obstacle estimation. The method further includes combining the vertical non-obstacle estimation and the horizontal non-obstacle estimation. The method additionally includes generating a non-obstacle map based on the combination of the vertical and horizontal non-obstacle estimations.

Performing vertical processing may include dividing the depth map into segments. At least one segment may include a number of pixels in a column. Linear model parameters may be estimated for at least one segment to determine the vertical non-obstacle estimation. A vertical reliability map that includes a reliability value for the vertical non-obstacle estimation may be generated.

Determining the vertical reliability map may include determining a segment fitting error for a given segment based on a difference between the estimated linear model parameters and pre-determined linear model parameters. A reliability value for the given segment may be determined by comparing the segment fitting error to a vertical estimation threshold. The reliability value for the given segment may be applied to at least one pixel in the given segment.

The pre-determined linear model parameters may be selected from among a plurality of road condition models. The plurality of road condition models may have a corresponding set of linear model parameters.

Performing horizontal processing may include obtaining a depth histogram for at least one row of pixels of the depth map. A terrain line may be determined from the depth histogram. A horizontal non-obstacle estimation may be determined based on a distance of a depth value of at least one pixel from the terrain line. A horizontal reliability map may be generated that includes a reliability value for the horizontal non-obstacle estimation.

Generating the horizontal reliability map may include determining whether the depth value of a given pixel is within a range of a mode of the depth histogram. The given pixel may have a high reliability value when the depth value of the given pixel is within the range of the mode of the depth histogram.

Combining the vertical non-obstacle estimation and the horizontal non-obstacle estimation may include performing both the vertical processing and the horizontal processing in parallel. The vertical non-obstacle estimation and the horizontal non-obstacle estimation may be merged based on a vertical reliability map and a horizontal reliability map.

A given pixel may be identified as a non-obstacle area in the non-obstacle map where both the vertical reliability map and the horizontal reliability map are characterized by a high reliability value for the given pixel. A given pixel may be identified as an obstacle area in the non-obstacle map where at least one of the vertical reliability map or the horizontal reliability map are characterized by a low reliability value for the given pixel. A given pixel may be identified as a non-obstacle area or obstacle area in the non-obstacle map based on a coordinate of the given pixel where the vertical reliability map and the horizontal reliability map are characterized by different reliability values for the given pixel.

Combining the vertical non-obstacle estimation and the horizontal non-obstacle estimation may include performing vertical processing of the depth map. A vertical reliability map may be obtained based on a model fitting confidence. Reliable regions of the vertical reliability map may be identified as non-obstacle areas. Horizontal processing may be performed on unreliable regions of the vertical reliability map to determine whether the unreliable regions are non-obstacle areas.

Combining the vertical non-obstacle estimation and the horizontal non-obstacle estimation may include performing horizontal processing of the depth map. A horizontal reliability map may be obtained based on a depth histogram distance. Reliable regions of the horizontal reliability map may be identified as non-obstacle areas. Vertical processing on unreliable regions of the horizontal reliability map may be performed to determine whether the unreliable regions are non-obstacle areas.

The non-obstacle map may be used in identifying a region of interest used by at least one of an object detection algorithm or a lane detection algorithm.

An electronic device is also described. The electronic device is configured to perform vertical processing of a depth map to determine a vertical non-obstacle estimation. The electronic device is also configured to perform horizontal processing of the depth map to determine a horizontal non-obstacle estimation. The electronic device is further configured to combine the vertical non-obstacle estimation and the horizontal non-obstacle estimation. The electronic device is additionally configured to generate a non-obstacle map based on the combination of the vertical and horizontal non-obstacle estimations.

An apparatus is also described. The apparatus includes means for performing vertical processing of a depth map to determine a vertical non-obstacle estimation. The apparatus also includes means for performing horizontal processing of the depth map to determine a horizontal non-obstacle estimation. The apparatus further includes means for combining the vertical non-obstacle estimation and the horizontal non-obstacle estimation. The apparatus additionally includes means for generating a non-obstacle map based on the combination of the vertical and horizontal non-obstacle estimations.

A computer-program product is also described. The computer-program product includes a non-transitory tangible computer-readable medium having instructions thereon. The instructions include code for causing an electronic device to perform vertical processing of a depth map to determine a vertical non-obstacle estimation. The instructions also include code for causing the electronic device to perform horizontal processing of the depth map to determine a horizontal non-obstacle estimation. The instructions further include code for causing the electronic device to combine the vertical non-obstacle estimation and the horizontal non-obstacle estimation. The instructions additionally include code for causing the electronic device to generate a non-obstacle map based on the combination of the vertical and horizontal non-obstacle estimations.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a block diagram illustrating an electronic device configured to perform non-obstacle area detection;

FIG. **2** is a block diagram illustrating a non-obstacle determination module;

FIG. **3** is a flow diagram illustrating a method for performing non-obstacle area detection;

FIGS. **4**A-**4**D illustrate an example of a vertical processing of a depth map;

FIG. **5** is a flow diagram illustrating a method for performing non-obstacle area detection using vertical processing;

FIGS. **6**A-**6**D illustrate an example of a horizontal processing of a depth map;

FIG. **7** is a flow diagram illustrating a method for performing non-obstacle area detection using horizontal processing;

FIG. **8** is a flow diagram illustrating a method for combining a vertical non-obstacle estimation and a horizontal non-obstacle estimation to determine a non-obstacle map;

FIG. **9** is a flow diagram illustrating another method for combining a vertical non-obstacle estimation and a horizontal non-obstacle estimation to determine a non-obstacle map;

FIG. **10** is a flow diagram illustrating yet another method for combining a vertical non-obstacle estimation and a horizontal non-obstacle estimation to determine a non-obstacle map;

FIGS. **11**A-**11**B illustrate an example of determining non-obstacle areas in an image;

FIGS. **12**A-**12**B illustrate another example of determining non-obstacle areas in an image;

FIGS. **13**A-**13**B illustrate an example of determining distance from a non-obstacle area;

FIG. **14** illustrates an example of using the non-obstacle map to identify a region of interest (ROI) used by an object detection algorithm;

FIG. **15** illustrates an example of using the non-obstacle map to identify a ROI used by a lane detection algorithm;

FIG. **16** is a flow diagram illustrating a method for classifying a road based on estimated linear model parameters; and

FIG. **17** illustrates certain components that may be included within an electronic device.

DETAILED DESCRIPTION

In many applications, it is advantageous to identify non-object areas within a region or environment for obstacle avoidance. For example, with advanced driver assistance systems (ADAS), it is important to identify the drivable area in front of the car for obstacle avoidance. Another scenario in which obstacle avoidance is important is vehicular automation in which an autonomous vehicle (e.g., an unmanned aerial vehicle (UAV) or autonomous automobile) senses its environment and navigates without human input.

Typically the problem of obstacle avoidance is looked at from the other direction, where objects of interest (e.g., pedestrians, cars, bicycles) are detected and may be identified via object detection/recognition algorithms and alerts are provided to the driver for taking precaution. For example, obstacle detection may be utilized to detect and identify traffic signs (e.g., speed limit signs, stop signs, street signs, etc.). However, this approach may be slow and inaccurate. Furthermore all the object classes have to be trained beforehand, which makes it difficult to ad din new object classes.

In the systems and methods described herein, instead of identifying objects, regions are identified that are free of obstacles or objects. These regions may be referred to as moveable areas. In other words, these three dimensional regions are non-obstacle areas in which movement is possible. For example, a non-obstacle area may be identified on a road. Upon identifying non-obstacle areas, various other applications such as road profiling, speed control, faster and more reliable object, and lane detection may be performed using the non-obstacle area.

The systems and methods described herein may be used to identify a non-obstacle area by analyzing a depth map. In an implementation, the depth map may be generated from a stereo image pair. In a road scenario, open space in the front may be mapped to a linear model that describes the road in the depth domain. By using the depth of road segments, linear model parameters may be estimated. The estimated linear model parameters may be compared with prior (e.g., pre-determined) model parameters. If fitting is achieved, then the segments are declared to be part of the open area. If a stereo image pair is not available, methods such as structure from motion can be used to obtain a depth map by using a mono camera input sequence.

The systems and methods described herein provide for the determination of a non-obstacle map based on an intelligent combination of vertical processing and horizontal processing of one or more images. Systems and methods of performing identifying a non-obstacle area are explained in greater detail below.

FIG. **1** is a block diagram illustrating an electronic device **102** configured to perform non-obstacle area detection. The electronic device **102** may also be referred to as a wireless communication device, a mobile device, mobile station, subscriber station, client, client station, user equipment (UE), remote station, access terminal, mobile terminal, terminal, user terminal, subscriber unit, etc. Examples of electronic devices include laptop or desktop computers, cellular phones, smart phones, wireless modems, e-readers, tablet devices, gaming systems, robots, aircraft, unmanned aerial vehicles (UAVs), automobiles, etc. Some of these devices may operate in accordance with one or more industry standards.

In many scenarios, the electronic device **102** may use a non-obstacle map **126** of a scene. In one example, a smartphone may generate a non-obstacle map **126** of a scene to identify unoccupied space. In another example, an automobile may include an advanced driver assistance system (ADAS) that may use a non-obstacle map **126** to regulate speed, steering, parking, etc., of the automobile based on detected traffic signs, signals and/or other objects. In another example, an unmanned aerial vehicle (UAV) may generate a non-obstacle map **126** from video recorded while in flight, may navigate based on detected objects (e.g., buildings, signs, people, packages, etc.), may pick up and/or deliver a detected package, etc. Many other examples may be implemented in accordance with the systems and methods disclosed herein. For instance, the systems and method disclosed herein could be implemented in a robot that performs one or more actions (e.g., fetching something, assembling something, searching for an item, etc.) based on one or more objects detected using the non-obstacle map **126**.

An electronic device **102** may include one or more cameras. A camera may include an image sensor **104** and an optical system **108** (e.g., lenses) that focuses images of objects that are located within the field of view of the optical system **108** onto the image sensor **104**. An electronic device **102** may also include a camera software application and a display screen. When the camera application is running, images **114** of objects that are located within the field of view of the optical system **108** may be recorded by the image sensor **104**. These images **114** may be stored in a memory buffer **112**. In some implementations, the camera may be separate from the electronic device **102** and the electronic device **102** may receive image data from one or more cameras external to the electronic device **102**.

Although the present systems and methods are described in terms of captured images **114**, the techniques discussed herein may be used on any digital image. Therefore, the terms video frame and digital image may be used interchangeably herein.

In many applications, it is beneficial for an electronic device **102** to identify areas that are free of obstacles. For example, in the case of ADAS, it is important to identify the drivable area in front of the car for obstacle avoidance. In some approaches, this problem is looked at from the other direction. In these approaches, objects of interest (e.g., pedestrians, cars, bicycles) are identified via object detection and recognition algorithms and alerts are provided to the driver for taking precaution.

Other approaches may determine non-obstacle areas by performing one of either vertical processing or horizontal processing of an image **114**. Each of the vertical processing and horizontal processing may estimate non-obstacle areas in an image **114**. However, each approach has limitations when performed independently.

Horizontal processing may give an incorrect non-obstacle estimation when a road is slanted. Vertical processing may perform segmentation on the image **114**. If the segments are large, then fitting is more reliable. However parts of objects could be included as non-obstacle (i.e., non-obstacle) areas as well. For example, using vertical processing, the bottom and top of cars or pedestrians may be incorrectly identified as a non-obstacle area. Also, sidewalks could be incorrectly identified as a non-obstacle area with the vertical processing approach. However, if segments are small, an inaccurate detection of non-obstacle area may occur.

The systems and methods described herein provide for the determination of a non-obstacle map **126** based on an intelligent combination of vertical processing and horizontal processing of one or more images **114**. In the described systems and methods, instead of identifying objects, a non-obstacle map **126** may be determined by combining vertical processing and horizontal processing of a depth map. In one implementation, the depth map may be obtained from one or more images. In another implementation, the depth map may be obtained from a depth data acquisition process (e.g., LIDAR).

In an implementation, the electronic device **102** may include a non-obstacle determination module **116** for determining a non-obstacle map **126**. The non-obstacle determination module **116** may include a depth map generator **118** for obtaining a depth map. The non-obstacle determination module **116** may also include a vertical estimation module **120** for performing vertical processing of the depth map to determine a vertical non-obstacle estimation. The non-obstacle determination module **116** may further include a horizontal estimation module **122** for performing horizontal processing of the depth map to determine a horizontal non-obstacle estimation.

An estimation combiner **124** may combine the vertical non-obstacle estimation and the horizontal non-obstacle estimation to determine a non-obstacle map **126**. In an implementation, the estimation combiner **124** may intelligently combine the vertical non-obstacle estimation and the horizontal non-obstacle estimation based on reliability values associated with the estimations. The non-obstacle map **126** may indicate which areas of the one or more images **114** are non-obstacle areas and which areas are obstacle areas. More detail on generating the non-obstacle map **126** is given in connection with FIG. **2**.

In an example, the non-obstacle map **126** may include non-obstacle areas that are free of obstacles (e.g., objects) on the roads. By combining the vertical processing and horizontal processing of an image **114**, false detections may be eliminated. Furthermore, a combined approach may provide a more reliable non-obstacle estimation.

The described systems and methods may be used to speed up various other applications. For example, the electronic device **102** may use the non-obstacle map **126** for other applications such as object detection, scene understanding, road profiling, and lane detection. The described systems and methods may also solve the problem of road curb detection that current lane detection algorithms cannot handle. The described systems and methods may further help in autonomous driving, where the speed is adjusted based on the terrain of the road.

FIG. **2** is a block diagram illustrating a non-obstacle determination module **216**. The non-obstacle determination module **216** may be implemented within an electronic or wireless device. The non-obstacle determination module **216** may include a depth map generator **218**, a vertical estimation module **220**, a horizontal estimation module **222** and an estimation combiner **224**. The non-obstacle determination module **216**, depth map generator **218**, a vertical estimation module **220**, a horizontal estimation module **222** and an estimation combiner **224** may be configurations of the non-obstacle determination module **116**, depth map generator **118**, a vertical estimation module **120**, a horizontal estimation module **122** and an estimation combiner **124** described above in connection with FIG. **1**.

The depth map generator **218** may receive one or more images **214**. In a configuration, the one or more images **214** may be obtained via a camera (e.g., an image sensor **104** and optical system **108**), as described in connection with FIG. **1**. In an implementation, the depth map generator **218** may receive a stereo image pair. In another implementation, the one or more images **214** may come from a video mono image. The image **214** may be a digital image made up of pixels.

The depth map generator **218** may obtain a depth map **230** from the one or more images **214**. The depth map **230** may include pixels **232** corresponding to the pixels of the one or more images **214**. Each pixel **232** in the depth map **230** has a depth value **234**. The depth value **234** indicates a distance of the pixel **232** relative to the camera. For example, a pixel **232** with a higher depth value **234** may indicate a closer proximity to the camera than a pixel **232** with a lower depth value **234**. An example of a depth map **230** is discussed in connection with FIGS. **4A-4D**.

It should be noted that the algorithm described herein does not require a depth value **234** for each pixel **232**. For example, the depth map **230** may have holes. The depth value **234** of these holes may be filled in before starting processing.

In the case of a stereo image pair, the depth map generator **218** may find the correspondence between pixels **232** to estimate a disparity. From the disparity, the depth map generator **218** may determine the depth value **234** for each pixel **232**. Alternatively, with a video mono image, the depth map generator **218** may determine the depth value **234** for each pixel **232** based on the motion of the video.

The depth map **230** may be provided to the vertical estimation module **220** and the horizontal estimation module **222**. The vertical estimation module **220** may perform vertical processing of the depth map **230** to determine a vertical non-obstacle estimation **242**. The horizontal estimation module **222** may perform horizontal processing of the depth map **230** to determine a horizontal non-obstacle estimation **258**.

The vertical estimation module **220** may divide the depth map **230** into segments **236**. Each segment **236** may include a number of pixels **232** in a column of the depth map **230**. In other words, the vertical estimation module **220** may process vertical segments **236** of the depth map **230**. A segment **236** may be a portion of a column of pixels **232** in the depth map **230**. For example, the segment **236** may be a vector of 10-15 pixels **232**. The segments **236** may or may not overlap.

The vertical estimation module **220** may estimate linear model parameters for each segment **236** to determine the vertical non-obstacle estimation **242**. Each segment **236** in the vertical direction may be estimated via a linear model. The linear model may be expressed as

$$y=p_1x+p_2, \tag{1}$$

where y is the depth value **234** of a pixel **232**, x is the coordinate of the pixel **232**, and p_1 and p_2 are the estimated linear model parameters **238**. If the estimation error is less than a vertical estimation threshold **246** and the linear fit has certain slope, it may be labelled as valid free space (a non-obstacle area **266**). In an implementation, a slope greater than 0 indicates non-obstacle, whereas a slope that is less than or equal to 0 indicates an object or obstacle. An example of this approach is discussed in connection with FIGS. **4A-4D**.

In matrix form, the linear model of Equation (1) is given by Equation (2).

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} x_1^1 \\ x_2^1 \\ x_3^1 \\ \vdots \\ x_n^1 \end{bmatrix} \times \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} \tag{2}$$

In Equation (2), y is an n-by-1 vector of depth values **234**, x is the n-by-2 design matrix (i.e., a matrix of n rows, 2 columns) for the model coordinates in the vertical dimension, and p_1 and p_2 are the estimated linear model parameters **238**. The value of n corresponds to the number of pixels **232** in the depth map segment **236**.

In one approach, p_1, and p_2 may be solved using a least-squares solution. In this approach, p is a vector of the unknown coefficients p_1, and p_2. The normal equations are given by

$$(X^TX)p=X^Ty \tag{3}$$

where X^T is the transpose of the design matrix X. Solving for p in Equation (4) results in the estimated linear model parameters **238** (i.e., p_1 and p_2).

$$p=(X^TX)^{-1}X^Ty \tag{4}$$

It should be noted that in an optimized implementation, the matrix inversion term $(X^TX)^{-1}X^T$ is fixed based on the location (i.e., the y-coordinate) and could be pre-calculated based on location and stored. Also, a piecewise linear model could estimate dips and bumps in a surface, with variation in p_1, p_2 and segment length. Furthermore, the primary complexity of this approach is due to matrix multiplication of two vectors of size n in the above Equation (2). In an example, n may be 10 or the chosen piecewise length instead of 10.

The vertical estimation module **220** may determine a vertical reliability map **248** a reliability value **250** for the vertical non-obstacle estimation **242**. In an implementation, the vertical estimation module **220** may determine a segment fitting error **244** for each segment **236** based on the difference between the estimated linear model parameters **238** and pre-determined linear model parameters **240**. The predetermined model parameters may be referred to as [pM1, pM2]. The vertical estimation module **220** may check how close the predetermined model parameters are to the estimated parameters [p_1, p_2] by comparing to a threshold (TH1). For example, $|p_1-pM1|<TH1$.

The vertical estimation threshold **246** may determine if the estimated linear model parameters **238** fit into the trained model parameters. The pre-determined linear model parameters **240** may be selected from among a plurality of road condition models. Each of the plurality of road condition models may have a corresponding set of linear model parameters **240**. Examples of the road condition models include a flat plane, hill, valley, etc. The pre-determined linear model parameters **240** may be determined by training.

The vertical estimation module **220** may determine an estimated depth value ($\hat{y}_i$) using the estimated linear model parameters **238** according to Equation (5), where $\hat{y}_i$ is the estimated depth value at the ith location.

$$\hat{y}_i = p_1 x_i + p_2 \tag{5}$$

A depth estimation error (e_i) with the estimated linear model parameters **238** may be determined according to Equation (6), where y_i is the depth value **234** at the ith location.

$$e_1 = y_i - \hat{y}_i \tag{6}$$

The segment fitting error **244** (s^2) may be determined according to Equation (7), where n is the length of the segment **236**.

$$s^2 = \sum_{i=1}^{n} \frac{e_i^2}{n-2} \tag{7}$$

The segment fitting error **244** may be used as a reliability metric for vertical processing. The vertical estimation module **220** may determine the vertical reliability value **250** for each segment **236** by comparing the segment fitting error **244** of each segment **236** to a vertical estimation threshold **246**.

The vertical estimation threshold **246** may be based on the pre-determined linear model parameters **240**. The vertical estimation threshold **246** may vary depending on which pre-determined linear model parameters **240** are used. For example, the vertical estimation threshold **246** may have one value if pre-determined linear model parameters **240** for a flat road are used. The vertical estimation threshold **246** may have a different value if pre-determined linear model parameters **240** for a hill are used.

The vertical estimation module **220** may check the absolute value of the difference between the segment fitting error **244** and the vertical estimation threshold **246**. A given segment **236** may have a high vertical reliability value **250** when the segment fitting error **244** for the given segment **236** is less than the vertical estimation threshold **246**. Conversely, the given segment **236** may have a low vertical reliability value **250** when the segment fitting error **244** for the given segment **236** is greater than or equal to the vertical estimation threshold **246**. Therefore, if the difference between the segment fitting error **244** and the vertical estimation threshold **246** is small, then the segment **236** is considered as part of a non-obstacle area **266**. If the difference is large, then the segment **236** is not considered as part of a non-obstacle area **266**.

Upon determining the reliability value **250** for a given segment **236**, the vertical estimation module **220** may threshold the vertical reliability map **248** to get a binary map. The reliability value **250** for a given segment **236** may be compared with a threshold to determine whether the segment **236** is a non-object area (e.g., movable) or an object area (e.g., non-moveable area). The vertical reliability map **248** may include the reliability values **250** of the pixels **232** in the depth map **230**. Therefore, the vertical reliability map **248** is a map that has a fitting confidence per depth pixel **232** as well as per segment **236**.

The horizontal estimation module **222** may perform horizontal processing of the depth map **230** to determine a horizontal non-obstacle estimation **258**. The horizontal processing may include obtaining a depth histogram **252** for each row of pixels **232** of the depth map **230**. An example of the depth histogram **252** is described in connection with FIGS. **6**A-**6**D. The depth histogram **252** may also be referred to as a disparity histogram.

In an implementation, the depth histogram **252** may be obtained by obtaining a histogram for each row in the depth map **230**. For example, for a row of pixels **232** from the depth map **230**, a histogram may be generated for the depth values **234** corresponding to the pixels **232** in the row.

The horizontal estimation module **222** may determine a terrain line **254** from the depth histogram **252**. The y-coordinate of the end points of the terrain line **254** determine the closest and farthest free space distance.

The terrain line **254** may be determined using a line extraction approach. A Hough transform may be applied on the depth histogram **252**. The Hough transform may extract multiple line segments from the depth histogram **252**. For example, the Hough transform may generate 10-20 small lines. The line segments may be merged to form the terrain line **254**. In an implementation, the angle of the terrain line **254** may be limited (e.g., between −20 degrees and −40 degrees) based on slope characteristics of non-obstacle space.

The horizontal estimation module **222** may determine the horizontal non-obstacle estimation **258** for each pixel **232** based on the distance of the depth value **234** of each pixel **232** from the terrain line **254**. A pixel **232** that has a depth value **234** that lies within a horizontal estimation threshold **260** of the terrain line **254** may be identified as a non-obstacle area **266**. For example, if the depth value **234** of a pixel **232** lies within a certain disparity range of the terrain line **254**, then that pixel **232** may be labeled as a non-obstacle area **266**. If the depth value **234** of a pixel **232** lies outside the certain disparity range of the terrain line **254**, then that pixel **232** may be labeled as an obstacle area **268**.

The horizontal estimation module **222** may also determine a horizontal reliability map **262** based on a depth histogram **252** distance. The horizontal reliability map **262** may include a reliability value **264** for the horizontal non-obstacle estimation **258** of each pixel **232**.

The distance to the mode **256** of the depth histogram **252** may be used as a reliability metric for the horizontal processing. The horizontal estimation module **222** may determine whether the depth value **234** of each pixel **232** is within a reliability threshold **261** of the mode **256** of the depth histogram **252**. A given pixel **232** may have a high reliability value **264** when the depth value **234** of the given pixel **232** is within the reliability threshold **261** of the mode **256** of the depth histogram **252**.

The estimation combiner **224** may combine the vertical non-obstacle estimation **242** and the horizontal non-obstacle estimation **258** to determine the non-obstacle map **226**. This combination may be based on the vertical reliability values **250** and the horizontal reliability values **264**. In one approach, the vertical processing and horizontal processing may be performed in parallel and the resulting non-obstacle estimations **242**, **258** merged. In another approach, the vertical processing and horizontal processing may be performed sequentially and the resulting non-obstacle estimations merged.

For the parallel processing approach, both the vertical processing and the horizontal processing may be performed in parallel. For example, the vertical estimation module **220** may perform vertical processing and the horizontal estimation module **222** may simultaneously perform horizontal processing as described above. The estimation combiner **224** may generate the non-obstacle map **226** by identifying each pixel **232** as a non-obstacle area **266** or obstacle area **268**.

This identification may be based on the vertical reliability values **250** of the vertical reliability map **248** and the horizontal reliability values **264** of the horizontal reliability map **262**.

If both the vertical reliability map **248** and the horizontal reliability map **262** indicate that a pixel **232** has a high reliability, then the pixel **232** may be identified as a non-obstacle area **266** in the non-obstacle map **226**. In other words, a given pixel **232** may be identified as a non-obstacle area **266** in the non-obstacle map **226** where both the vertical reliability map **248** and the horizontal reliability map **262** are characterized by a high reliability value for the given pixel **232**.

In an implementation, this may be achieved by thresholding the vertical reliability map **248** and the horizontal reliability map **262** with a respective threshold. For example, if a vertical reliability value **250** and a horizontal reliability value **264** of a given pixel **232** are greater than a threshold, then the pixel **232** may be identified as a non-obstacle area **266**. In the case of both the vertical reliability map **248** and the horizontal reliability map **262** indicating low reliability, the pixel **232** may be labeled as an obstacle area **268**.

For the case where either of the vertical reliability map **248** or the horizontal reliability map **262** indicates a high reliability and the other indicates a low reliability, one or more different merging approaches may be performed. In one approach, if at least one of the vertical reliability map **248** or the horizontal reliability map **262** indicates that the given pixel **232** has a low reliability, then the given pixel **232** is identified as an obstacle area **268** in the non-obstacle map **226**. In other words, a given pixel **232** may be identified as an obstacle area **268** in the non-obstacle map **226** where at least one of the vertical reliability map **248** or the horizontal reliability map **262** are characterized by a low reliability value for the given pixel **232**. In this approach, if one of the reliability maps **248**, **262** is indicating low reliability, the pixel **232** may be labeled based only on that reliability map **248**, **262**.

In another approach, the vertical reliability map **248** and the horizontal reliability map **262** are characterized by different reliability values **250**, **264** for a given pixel **232**. In this case, the given pixel **232** may be identified as a non-obstacle area **266** or obstacle area **268** based on the coordinate of the given pixel **232**. In this approach, if both reliability maps **248**, **262** are close to each other in terms of reliability (e.g., one being higher than other), the decision can be further enhanced by considering the pixel **232** coordinates.

In an example, RHij is the horizontal reliability value **264** for ith and jth pixel **232** from horizontal processing, and RVij is the vertical reliability value **250** from vertical processing (where both reliability values **250**, **264** are normalized if obtained by different methods). If $|RHij-RVij|<TH$, then this will indicate closeness of reliability maps **248**, **262**. Furthermore, RHij could be compared to RVi+n,j+n, where n is $<N$ (for e.g. N=5 for 720p resolution).

For the sequential processing approach, either vertical processing or horizontal processing may be performed first. After the first processing is performed, the reliability map (e.g., either the vertical reliability map **248** or the horizontal reliability map **262**) may be calculated for whole depth map **230**. For pixels **232** where reliability is not met, a second processing is called. The results of the first and second processing may be merged to obtain the non-obstacle map **226**. An example of sequential processing starting with vertical processing is described in connection with FIG. **9**. An example of sequential processing starting with horizontal processing is described in connection with FIG. **10**.

The non-obstacle determination module **216** may perform additional processing of the non-obstacle map **226**. In an implementation, the non-obstacle determination module **216** may perform outlier removal. For example, a small number of pixels **232** may be incorrectly labeled obstacle area **268** within a non-obstacle area **266**. The non-obstacle determination module **216** may identify these outliers and change their status to either non-obstacle of obstacle. The non-obstacle determination module **216** may perform additional filtering of the non-obstacle map **226** to prepare it for subsequent operations.

The non-obstacle map **226** may be used for different operations. In one implementation, the non-obstacle map **226** may be used to identify a region of interest used by an object detection algorithm. This may be accomplished as described in connection with FIG. **14**. In another implementation, the non-obstacle map **226** may be used to identify a region of interest used by a lane detection algorithm. This may be accomplished as described in connection with FIG. **15**.

As illustrated in FIG. **2**, one or more of the illustrated components may be optionally implemented by a processor **228**. For example, the non-obstacle determination module **216** may be implemented by a processor **228**. In some configurations, different processors may be used to implement different components (e.g., one processor may implement the depth map generator **218**, another processor may be used to implement the vertical estimation module **220**, another processor may be used to implement the horizontal estimation module **222** and yet another processor may be used to implement the estimation combiner **224**).

It should be noted that it is possible that to rotate the image **214** and perform diagonal processing. If an image **214** is rotated, the vertical and horizontal processing may become diagonal processing. Therefore, while the terms vertical and horizontal processing are used herein, it may be recognized that processing could be applied across a different section through the rotated image with corresponding coordinate mapping.

FIG. **3** is a flow diagram illustrating a method **300** for performing non-obstacle area detection. The method **300** may be implemented by, with reference to FIG. **1**, an electronic device **102**, e.g., a non-obstacle determination module **116**. The electronic device **102** may obtain **302** a depth map **230** from one or more images **214**. In one implementation, the electronic device **102** may generate the depth map **230** from a stereo image pair. In another implementation, the electronic device **102** may generate the depth map **230** from a video mono image. Each pixel **232** in the depth map **230** may have a depth value **234**.

The electronic device **102** may perform **304** vertical processing of the depth map **230** to determine a vertical non-obstacle estimation **242**. The vertical processing may include dividing the depth map **230** into segments **236**. Each segment **236** may include a number of pixels **232** in a column. The electronic device **102** may estimate linear model parameters **238** for each segment **236** to determine the vertical non-obstacle estimation **242**. The electronic device **102** may determine a vertical reliability map **248** that includes a reliability value **250** for the vertical non-obstacle estimation **242**.

The electronic device **102** may perform **306** horizontal processing of the depth map **230** to determine a horizontal non-obstacle estimation **258**. The horizontal processing may include obtaining a depth histogram **252** for each row of pixels **232** of the depth map **230**. The electronic device **102** may determine a terrain line **254** from the depth histogram **252**. The electronic device **102** may determine the horizontal non-obstacle estimation **258** for each pixel **232** based on the distance of the depth value **234** of each pixel **232** from the terrain line **254**. The electronic device **102** may also determine a horizontal reliability map **262** that includes a reliability value **264** for the horizontal non-obstacle estimation **258** of each pixel **232**.

The electronic device **102** may combine **308** the vertical non-obstacle estimation **242** and the horizontal non-obstacle estimation **258** to determine a non-obstacle map **226**. In one implementation, the electronic device **102** may perform parallel vertical processing and horizontal processing. In this implementation, the electronic device **102** may combine the vertical non-obstacle estimation **242** and the horizontal non-obstacle estimation **258**, as described in connection with FIG. **10**. In another implementation, the electronic device **102** may perform sequential processing starting with vertical processing, as described in connection with FIGS. **11**A-**11**B. In yet another implementation, the electronic device **102** may perform sequential processing starting with horizontal processing, as described in connection with FIGS. **12**A-**12**B.

FIGS. **4**A-**4**D illustrate an example of a vertical processing of a depth map **430**. The depth map **430** may be generated from one or more images **404**. The depth map **430** may include locations corresponding to the pixels of the original image(s) **404**. Each location (e.g., coordinate) in the depth map **430** may have a horizontal coordinate **472** and a vertical coordinate **474***a* corresponding to the pixels of the original image(s) **404**.

The depth map **430** may match the size of the original image **404** if the depth is calculated from the original resolution. In the visualization of a depth map **430**, the depth value **434** may be obtained from the corresponding coordinates of the original image **404**. It should be noted that a visualization of the depth map **430** may or may not be generated when generating a non-obstacle map **226**.

Each pixel **232** of the depth map **430** may have a depth value **434**. In this example, the depth values **434***a* may range from 0 to 120, where 0 indicates the farthest distance and 120 indicates the nearest distance. It should be noted that different values may be used for the depth values **434**.

In an implementation, the disparity to depth mapping can be explained by the following equations. Z=fBld, where Z is the distance along the camera Z axis, f is the focal length (in pixels), B is the baseline (in meters), d is the disparity (in pixels). When the disparity is small, the depth is large. The depth can be found in terms of meters.

It should be noted that depth estimation algorithms from stereo images **404** may not be completely reliable. For example, a depth estimation algorithm might not be able to assign depth values **434** in certain regions. A depth filling algorithm may be used to fill in the missing depth values **434**. For example the neighboring depth value **434** may be propagated to an adjoining area. The propagation may be from left or from right. Alternatively, missing depth values **434** may be filled by interpolating between left and right, as well as top and bottom.

This example shows a first column **470***a* and a second column **470***b*. In a first column graph **475***a*, the depth values **434***b* are shown for the pixels **232** in the first column **470***a*. In this first column graph **475***a*, the depth values **434***b* are plotted verses the vertical coordinates **474***b* of the pixels **232** from the first column **470***a*. It should be noted that in this example, the zero values from 0 to 40 and after 400 pixels is because there is no depth assigned there. Because stereo images may be calibrated, they may not have the matching field of view (FOV) after calibration. Depth estimation may only be performed only within same FOV.

In a second column graph **475***b*, the depth values **434***c* are shown for the pixels **232** in the second column **470***b*. In this second column graph **475***b*, the depth values **434***c* are plotted verses the vertical coordinates **474***c* of the pixels **232** from the second column **470***b*. The dashed line from 0 to 150 is the mapping showing the algorithm result. The mapping may only be to sloped (i.e., slanted) lines (which specify a non-object road area). To map to objects (which are flat lines), then the same algorithm may be used, but the mapping parameters may be changed.

The solid line in the graphs **475***a,b* comes from original depth values. The dashed line is generated according to the described systems and methods. It should be noted that the mapping may be based on the slope of the dashed line. In these graphs **475***a,b*, a slope greater than 0 indicates a non-obstacle area **266**. A slope less than or equal to 0 indicates an obstacle area **268**.

During vertical processing, the electronic device **102** may divide the depth map **430** into segments **236**. Each segment **236** may include a number of pixels **232** in a column **470**. For example, the segment **236** may be a vector of 10-15 pixels **232**. The electronic device **102** may determine a vertical non-obstacle estimation **242** and may estimate linear model parameters **238** as described in connection with FIG. **2**. If the estimation error is less than a threshold **246** and the linear fit has a certain slope, then the segment **236** may be labelled as a valid non-obstacle area **266**.

FIG. **5** is a flow diagram illustrating a method **500** for performing non-obstacle area detection using vertical processing. The method **500** may be implemented by an electronic device **102**, e.g., a non-obstacle determination module **116**. The electronic device **102** may divide **502** a depth map **430** into segments **236**. Each segment **236** may include a number n of pixels **232** in a column **470**. In an implementation, n may equal 10 pixels **232**.

The electronic device **102** may estimate **504** linear model parameters **238** for each segment **236** to determine the vertical non-obstacle estimation **242**. This may be accomplished according to Equations 1-4 described above.

The electronic device **102** may determine **506** a vertical reliability map **248** that includes a reliability value **250** for the vertical non-obstacle estimation **242**. For example, the electronic device **102** may determine a segment fitting error **244** for each segment **236** based on the difference between the estimated linear model parameters **238** and pre-determined linear model parameters **240**. The segment fitting error **244** may be determined according to Equations 5-7 above. The pre-determined linear model parameters **240** may be selected from among a plurality of road condition models (e.g., flat, hill, valley). Each of the plurality of road condition models may have a corresponding set of linear model parameters **240**.

The electronic device **102** may determine the reliability value **250** for each segment **236** by comparing the segment fitting error **244** of each segment **236** to a vertical estimation threshold **246**. A given segment **236** may have a high reliability value **250** when the segment fitting error **244** for the given segment **236** is less than the vertical estimation threshold **246**.

The electronic device **102** may apply the reliability value **250** for a given segment **236** to each pixel **232** in the given segment **236**. Therefore, each pixel **232** in the vertical reliability map **248** may have a reliability value **250** indicating confidence in the vertical non-obstacle estimation **242**.

FIGS. **6**A-**6**D illustrate an example of a horizontal processing of a depth map **630**. The depth map **630** may be generated from one or more images **114**. The depth map **630** illustrated in FIG. **6**A is the same depth map **430** described in connection with FIG. **4**B (compressed to fit the page). The depth map **630** may include locations corresponding to the pixels of the original image(s) **114**. Each location in the depth map **630** may have a horizontal coordinate **672** and a vertical coordinate **674** corresponding to the pixels **232** of the original image(s) **114**.

The electronic device **102** may generate a depth histogram **652**. The depth histogram **652** may be generated by obtaining a histogram of depths for each row in the depth map **630**. For example, the depth histogram **652** may be generated by projecting the depth map **630** in the vertical axis.

A depth histogram **652** may be calculated for each row in an image **114**. The number of bins in the depth histogram **652** corresponds to the number of maximum disparity values in the image **114**. For example, it could be 150 for a 720p image, or it could be larger for a larger resolution image and smaller for a smaller resolution image. The x axis in the right side of FIG. **6**B corresponds to disparity values, and the intensity value in the image **114** corresponds to the histogram count for that disparity value. The darker the shade it is, the higher the disparity value, the lighter the shade it is, the lower the disparity value of histogram. In this example, a maximum number of disparity bins is 150. In the depth histogram **652**, disparity values are plotted versus the vertical coordinates **674**.

The electronic device **102** may apply a Hough transform on the depth histogram **652** to extract line segments **676**. The Hough transform may extract multiple line segments **676** from the depth histogram **252**. For example, the Hough transform may generate 10-20 small line segments **676**.

The line segments **676** may be merged to form the terrain line **654**. The x-coordinate of the end points of the terrain line **254** determine the closest and farthest free space distance. In an implementation, the angle of the terrain line **254** may be limited (e.g., between −20 degrees and −40 degrees) as non-obstacle space has certain slope characteristics.

If the depth histogram **652** gives a line with a negative slope, it corresponds to a road segment in front of the car without any obstacles. An obstacle will be represented by a straight vertical line at 90 degrees. The terrain line **254** indicates that the depth values in front of the camera are slowly decreasing as the depth values are analyzed in rows of an image **114**. If there is an object, then the object will have same depth value for a certain number of rows. In this case, depth values will not be decreasing. The slope (i.e., angle of the terrain line **254**) may be chosen according to the maximum slope a road can have.

The electronic device **102** may label the pixels **232** with depth values **634** that lie within a horizontal estimation threshold **260** of the terrain line **654** as non-obstacle areas **266**. Those pixels **232** with depth values **634** that lie outside the horizontal estimation threshold **260** of the terrain line **654** may be labeled as obstacle areas **268**.

FIG. **7** is a flow diagram illustrating a method **700** for performing non-obstacle area detection using horizontal processing. The method **700** may be implemented by an electronic device **102**, e.g., a non-obstacle determination module **116**. The electronic device **102** may obtain **702** a depth histogram **252** for each row of pixels **232** of the depth map **230**. This may be accomplished as described in connection with FIGS. **6**A-**6**D.

The electronic device **102** may determine **704** a terrain line **254** from the depth histogram **252**. This may be accomplished as described in connection with FIGS. **6**A-**6**D.

The electronic device **102** may determine **706** a horizontal non-obstacle estimation **258** for each pixel **232** based on the distance of the depth value **234** of each pixel **232** from the terrain line **254**. Those pixels **232** with depth values **634** that lie within a horizontal estimation threshold **260** of the terrain line **654** may be labeled as non-obstacle areas **266**. Those pixels **232** with depth values **634** that lie outside the horizontal estimation threshold **260** of the terrain line **654** may be labeled as obstacle areas **268**.

The electronic device **102** may determine **708** a horizontal reliability map **262** that includes a reliability value **264** for the horizontal non-obstacle estimation **258** of each pixel **232**. For example, the distance to the mode **256** of the depth histogram **252** may be used as a reliability metric for the horizontal processing. The electronic device **102** may determine whether the depth value **234** of each pixel **232** is within a reliability threshold **261** of the mode **256** of the depth histogram **252**. A given pixel **232** may have a high reliability value **264** when the depth value **234** of the given pixel **232** is within the reliability threshold **261** of the mode **256** of the depth histogram **252**.

FIG. **8** is a flow diagram illustrating a method **800** for combining a vertical non-obstacle estimation **242** and a horizontal non-obstacle estimation **258** to determine a non-obstacle map **226**. The method **800** may be implemented by an electronic device **102**, e.g., a non-obstacle determination module **116**. In this method **800**, the electronic device **102** may perform vertical processing and horizontal processing in parallel.

The electronic device **102** may perform **802** vertical processing of a depth map **230** to determine a vertical non-obstacle estimation **242**. This may be accomplished as described in connection with FIG. **5**.

The electronic device **102** may obtain **804** a vertical reliability map **248** based on a model fitting confidence. This may be accomplished as described in connection with FIG. **5**.

The electronic device **102** may perform **806** horizontal processing of the depth map **230** to determine a horizontal non-obstacle estimation **258**. This may be accomplished as described in connection with FIG. **7**.

The electronic device **102** may obtain **808** a horizontal reliability map **262** based on a depth histogram **252** distance. This may be accomplished as described in connection with FIG. **7**.

It should be noted that steps **802**, **804**, **806**, **808** may be performed in parallel. For example, while the electronic device **102** performs the vertical processing steps **802** and **804**, the electronic device **102** may simultaneously perform the horizontal processing steps **806** and **808**.

The electronic device **102** may merge **810** the vertical non-obstacle estimation **242** and the horizontal non-obstacle estimation **258** to obtain the non-obstacle map **226**. This merge may be based on the vertical reliability map **248** and the horizontal reliability map **262**.

If both the vertical reliability map **248** and the horizontal reliability map **262** indicate that a pixel **232** has a high reliability, then the pixel **232** may be identified as a non-obstacle area **266** in the non-obstacle map **226**. For example, if the vertical reliability map **248** indicates a high vertical reliability value **250** and the horizontal reliability map **262** indicates a high horizontal reliability value **264**, then the pixel **232** may be labeled as a non-obstacle area **266** in the non-obstacle map **226**.

For the case where either of the vertical reliability map **248** or the horizontal reliability map **262** indicates a high reliability and the other indicates a low reliability, one or more different merging approaches may be performed. In one approach, if at least one of the vertical reliability map **248** or the horizontal reliability map **262** indicates that the given pixel **232** has a low reliability value **250**, **264**, then the given pixel **232** is identified as an obstacle area **268** in the non-obstacle map **226**. In another approach, the vertical reliability map **248** and the horizontal reliability map **262** may indicate different reliability values **250**, **264**. In this case, the given pixel **2332** may be identified as a non-obstacle area **266** or obstacle area **268** based on the coordinate of the given pixel **232**.

FIG. **9** is a flow diagram illustrating another method **900** for combining a vertical non-obstacle estimation **242** and a horizontal non-obstacle estimation **258** to determine a non-obstacle map **226**. The method **900** may be implemented by an electronic device **102**, e.g., a non-obstacle determination module **116**. In this method **900**, the electronic device **102** may perform a sequential application of vertical processing followed by horizontal processing.

The electronic device **102** may perform **902** vertical processing of a depth map **230** to determine a vertical non-obstacle estimation **242**. This may be accomplished as described in connection with FIG. **5**.

The electronic device **102** may obtain **904** a vertical reliability map **248** based on a model fitting confidence. This may be accomplished as described in connection with FIG. **5**.

The electronic device **102** may identify **906** reliable regions as non-obstacle areas **266** based on the vertical reliability map **248**. For example, each pixel **232** that has a high vertical reliability value **250** in the vertical reliability map **248** may be labeled as a non-obstacle area **266** in the non-obstacle map **226**.

The electronic device **102** may perform **908** horizontal processing on unreliable regions of the vertical reliability map **248** to determine whether the unreliable regions are non-obstacle areas **266**. For example, the electronic device **102** may perform horizontal processing on at least one row of pixels **232** that have a low reliability value **250**. It should be noted that the length of a row could be as wide as the image **114** or could be shorter than the image width. The horizontal processing may be accomplished as described in connection with FIG. **7** to determine a horizontal non-obstacle estimation **258**. The non-obstacle map **226** may be updated based on the results of the horizontal reliability map **262** of the unreliable regions.

FIG. **10** is a flow diagram illustrating yet another method **1000** for combining a vertical non-obstacle estimation **242** and a horizontal non-obstacle estimation **258** to determine a non-obstacle map **226**. The method **1000** may be implemented by an electronic device **102**, e.g., a non-obstacle determination module **116**. In this method **1000**, the electronic device **102** may perform a sequential application of horizontal processing followed by vertical processing.

The electronic device **102** may perform **1002** horizontal processing of a depth map **230** to determine a horizontal non-obstacle estimation **258**. This may be accomplished as described in connection with FIG. **7**.

The electronic device **102** may obtain **1004** a horizontal reliability map **262** based on a depth histogram **252** distance. This may be accomplished as described in connection with FIG. **7**.

The electronic device **102** may identify **1006** reliable regions as non-obstacle areas **266** based on the horizontal reliability map **262**. For example, each pixel **232** that has a high horizontal reliability value **264** in the horizontal reliability map **262** may be labeled as a non-obstacle area **266** in the non-obstacle map **226**.

The electronic device **102** may perform **1008** vertical processing on unreliable regions of the horizontal reliability map **262** to determine whether the unreliable regions are non-obstacle areas **266**. For example, the electronic device **102** may perform vertical processing on one or more column(s) of pixels **232** that have a low horizontal reliability value **264**. The one or more column(s) of pixels **232** may be as tall as the image **114** or could be less than the image height.

The vertical processing may be accomplished as described in connection with FIG. **5** to determine a vertical non-obstacle estimation **242**. The non-obstacle map **226** may be updated based on the results of the vertical reliability map **248** of the unreliable regions.

FIGS. **11A-11B** illustrate an example of determining non-obstacle areas **1166** in an image **1114**. In this example, the original image **1114***a* is an image of a one-way road.

The processed image **1114***b* shows the non-obstacle area **1166** that is determined according to the systems and methods described herein. The processed image **1114***b* shows an example from an intermediate step of the algorithm, not the final result. This is to show there could be holes in the non-obstacle map **126** that should be further processed. Also this illustrates the result from vertical processing alone.

The non-obstacle area **1166** includes the open area corresponding to the road. Certain outlier areas **1178** in non-obstacle area **1166** were not identified as part of the non-obstacle area **1166**. As used herein, outlier means that the depth values in the image **1114***b* did not fit in the predetermined model. This may be due to a possible wrong estimation of depth values (e.g., input depth values may not be perfect), so some areas appear as holes (or outliers). These outlier areas **1178** may be removed by performing additional processing of the image **1114**.

FIGS. **12A-12B** illustrate another example of determining non-obstacle areas **1266** in an image **1214**. In this example, the original image **1214***a* is an image of an intersection. The processed image **1214***b* shows the non-obstacle area **1266** that is determined according to the systems and methods described herein.

FIGS. **13A-13B** illustrate an example of determining distance **1380** from a non-obstacle area **1366**. This example shows the processed image **1314** of the road described in connection with FIGS. **11A-11B**. The non-obstacle area **1366** is determined according to the systems and methods described herein.

In the depth map **1330** of FIG. **13B**, the x and y coordinates are the coordinate positions and the shading is indicative of depth. In this example, the depth map **1330** includes the depth information for the non-obstacle area **1366**. The depth map **1330** indicates how far there will be free space in front of the camera.

Using the depth values **234** from the depth map **1330**, the electronic device **102** may determine various distances associated with the non-obstacle area **1366***b*. For example, the electronic device **102** may determine that the farthest distance in the non-obstacle area **1366***b* is between 45-50 meters away from the image sensor **104**. Similarly, the electronic device **102** may determine that the nearest cars are approximately 11 meters from the image sensor **104**.

FIG. **14** illustrates an example of using the non-obstacle map **226** to identify a region of interest (ROI) **1482** used by an object detection algorithm. This example shows the processed image **1414** of the road described in connection with FIGS. **11**A-**11**B. The non-obstacle area **1466** is determined according to the systems and methods described herein.

The electronic device **102** may then identify one or more ROI **1482** for a potential obstacle area **268**. For example, the electronic device **102** may identify obstacle areas **268** from the non-obstacle map **226**. In an implementation, pixels **232** that are not labeled as non-obstacle area **1466** may be identified as an obstacle area **268**. These obstacle areas **268** may be included in one or more ROIs **1482**. In this example, the electronic device **102** identifies four ROIs **1482***a-d* as potential object areas.

The electronic device **102** may run an object detector in the identified ROIs **1482**. For example, the electronic device **102** may detect whether an ROI **1482** includes a car, traffic signal, a pedestrian, lanes, curbs, etc.

Identifying the non-obstacle area **1466** first results in a reduced search area for the object detection. This may reduce the amount of processing that is performed for object detection.

FIG. **15** illustrates an example of using the non-obstacle map **226** to identify a region of interest (ROI) **1582** used by a lane detection algorithm. This example shows the processed image **1514** of a road. The non-obstacle area **1566** is determined according to the systems and methods described herein.

The electronic device **102** may then identify one or more ROI **1582** for road sides and/or curbs. For example, the electronic device **102** may identify obstacle areas **268** from the non-obstacle map **226**. In this example, the electronic device **102** identifies two ROIs **1582***a-b* on the sides of the non-obstacle area **1566** as potential road sides and/or curbs.

The electronic device **102** may run a lane detector in the identified ROIs **1582***a-b*. Identifying the non-obstacle area **1566** first results in a reduced search area for the lane detection. This may reduce the amount of processing that is performed for lane detection.

FIG. **16** is a flow diagram illustrating a method **1600** for classifying a road based on estimated linear model parameters **238**. The method **1600** may be implemented by an electronic device **102**, e.g., a non-obstacle determination module **116**.

The electronic device **102** may obtain **1602** a depth map **230** of a road image **114**. The depth map **230** may be generated as described in connection with FIG. **2**.

The electronic device **102** may perform **1604** segment fitting to estimate linear model parameters **238**. The estimated linear model parameters **238** may be determined as described in connection with FIG. **2**.

The electronic device **102** may classify **1606** the road based on the estimated linear model parameters **238**. For example, the electronic device **102** may compare the estimated linear model parameters **238** with a plurality of pre-determined linear model parameters **240**. As described above, the pre-determined linear model parameters **240** may be associated with a plurality of road condition models. Each of the plurality of road condition models may have a corresponding set of linear model parameters **240**. Examples of the road condition models include a flat plane, slope (e.g., hill), valley, irregular road, etc.

In an implementation, the pre-determined linear model parameters **240** can be obtained via training. Pre-labeled test data can be used, where pre-labeled refers to labeled images **114** and depth maps **230** of flat roads, or irregular roads, etc. With this data the pre-determined linear model parameters **240** may be generated.

The electronic device **102** may determine which of the pre-determined linear model parameters **240** best fit the estimated linear model parameters **238**. The road may be classified **1606** according to the road condition model that best fits the estimated linear model parameters **238**. Therefore, by classifying **1606** the road, the electronic device **102** may determine the type of free space in the road image **114**.

FIG. **17** illustrates certain components that may be included within an electronic device **1702**. The electronic device **1702** may be or may be included within a camera, video camcorder, digital camera, cellular phone, smart phone, computer (e.g., desktop computer, laptop computer, etc.), tablet device, media player, television, automobile, personal camera, action camera, surveillance camera, mounted camera, connected camera, robot, aircraft, drone, unmanned aerial vehicle (UAV), healthcare equipment, gaming console, personal digital assistants (PDA), set-top box, etc. The electronic device **1702** includes a processor **1728**. The processor **1728** may be a general purpose single- or multi-chip microprocessor (e.g., an ARM), a special purpose microprocessor (e.g., a digital signal processor (DSP)), a microcontroller, a programmable gate array, etc. The processor **1728** may be referred to as a central processing unit (CPU). Although just a single processor **1728** is shown in the electronic device **1702**, in an alternative configuration, a combination of processors (e.g., an ARM and DSP) could be used.

The electronic device **1702** also includes memory **1739**. The memory **1739** may be any electronic component capable of storing electronic information. The memory **1739** may be embodied as random access memory (RAM), read-only memory (ROM), magnetic disk storage media, optical storage media, flash memory devices in RAM, on-board memory included with the processor, EPROM memory, EEPROM memory, registers, and so forth, including combinations thereof.

Data **1721***a* and instructions **1741***a* may be stored in the memory **1739**. The instructions **1741***a* may be executable by the processor **1728** to implement one or more of the methods described herein. Executing the instructions **1741***a* may involve the use of the data that is stored in the memory **1739**. When the processor **1728** executes the instructions **1741**, various portions of the instructions **1741***b* may be loaded onto the processor **1728**, and various pieces of data **1721***b* may be loaded onto the processor **1728**.

The electronic device **1702** may also include a transmitter **1725** and a receiver **1727** to allow transmission and reception of signals to and from the electronic device **1702**. The transmitter **1725** and receiver **1727** may be collectively referred to as a transceiver **1729**. One or multiple antennas **1737***a-b* may be electrically coupled to the transceiver **1729**. The electronic device **1702** may also include (not shown) multiple transmitters, multiple receivers, multiple transceivers and/or additional antennas.

The electronic device **1702** may include a digital signal processor (DSP) **1731**. The electronic device **1702** may also include a communications interface **1733**. The communications interface **1733** may allow enable one or more kinds of input and/or output. For example, the communications interface **1733** may include one or more ports and/or communication devices for linking other devices to the electronic device **1702**. Additionally or alternatively, the communications interface **1733** may include one or more other interfaces (e.g., touchscreen, keypad, keyboard, microphone, camera, etc.). For example, the communication interface **1733** may enable a user to interact with the electronic device **1702**.

The various components of the electronic device **1702** may be coupled together by one or more buses, which may include a power bus, a control signal bus, a status signal bus, a data bus, etc. For the sake of clarity, the various buses are illustrated in FIG. **17** as a bus system **1723**.

In accordance with the present disclosure, a circuit, in an electronic device, may be adapted to obtain a depth map from one or more images. Each pixel in the depth map may have a depth value. The same circuit, a different circuit, or a second section of the same or different circuit may be adapted to perform vertical processing of the depth map to determine a vertical non-obstacle estimation. The same circuit, a different circuit, or a third section of the same or different circuit may be adapted to perform horizontal processing of the depth map to determine a horizontal non-obstacle estimation. The same circuit, a different circuit, or a fourth section of the same or different circuit may be adapted to combine the vertical non-obstacle estimation and the horizontal non-obstacle estimation to determine a non-obstacle map. In addition, the same circuit, a different circuit, or a fifth section of the same or different circuit may be adapted to control the configuration of the circuit(s) or section(s) of circuit(s) that provide the functionality described above.

The term "determining" encompasses a wide variety of actions and, therefore, "determining" can include calculating, computing, processing, deriving, investigating, looking up (e.g., looking up in a table, a database or another data structure), ascertaining and the like. Also, "determining" can include receiving (e.g., receiving information), accessing (e.g., accessing data in a memory) and the like. Also, "determining" can include resolving, selecting, choosing, establishing and the like.

The phrase "based on" does not mean "based only on," unless expressly specified otherwise. In other words, the phrase "based on" describes both "based only on" and "based at least on."

The term "processor" should be interpreted broadly to encompass a general purpose processor, a central processing unit (CPU), a microprocessor, a digital signal processor (DSP), a controller, a microcontroller, a state machine, and so forth. Under some circumstances, a "processor" may refer to an application specific integrated circuit (ASIC), a programmable logic device (PLD), a field programmable gate array (FPGA), etc. The term "processor" may refer to a combination of processing devices, e.g., a combination of a DSP and a microprocessor, a plurality of microprocessors, one or more microprocessors in conjunction with a DSP core, or any other such configuration.

The term "memory" should be interpreted broadly to encompass any electronic component capable of storing electronic information. The term memory may refer to various types of processor-readable media such as random access memory (RAM), read-only memory (ROM), non-volatile random access memory (NVRAM), programmable read-only memory (PROM), erasable programmable read-only memory (EPROM), electrically erasable PROM (EEPROM), flash memory, magnetic or optical data storage, registers, etc. Memory is said to be in electronic communication with a processor if the processor can read information from and/or write information to the memory. Memory that is integral to a processor is in electronic communication with the processor.

The terms "instructions" and "code" should be interpreted broadly to include any type of computer-readable statement (s). For example, the terms "instructions" and "code" may refer to one or more programs, routines, sub-routines, functions, procedures, etc. "Instructions" and "code" may comprise a single computer-readable statement or many computer-readable statements.

The functions described herein may be implemented in software or firmware being executed by hardware. The functions may be stored as one or more instructions on a computer-readable medium. The terms "computer-readable medium" or "computer-program product" refers to any tangible storage medium that can be accessed by a computer or a processor. By way of example, and not limitation, a computer-readable medium may comprise RAM, ROM, EEPROM, CD-ROM or other optical disk storage, magnetic disk storage or other magnetic storage devices, or any other medium that can be used to carry or store desired program code in the form of instructions or data structures and that can be accessed by a computer. Disk and disc, as used herein, includes compact disc (CD), laser disc, optical disc, digital versatile disc (DVD), floppy disk and Blu-ray® disc where disks usually reproduce data magnetically, while discs reproduce data optically with lasers. It should be noted that a computer-readable medium may be tangible and non-transitory. The term "computer-program product" refers to a computing device or processor in combination with code or instructions (e.g., a "program") that may be executed, processed or computed by the computing device or processor. As used herein, the term "code" may refer to software, instructions, code or data that is/are executable by a computing device or processor.

Software or instructions may also be transmitted over a transmission medium. For example, if the software is transmitted from a website, server, or other remote source using a coaxial cable, fiber optic cable, twisted pair, digital subscriber line (DSL), or wireless technologies such as infrared, radio and microwave, then the coaxial cable, fiber optic cable, twisted pair, DSL, or wireless technologies such as infrared, radio and microwave are included in the definition of transmission medium.

The methods disclosed herein comprise one or more steps or actions for achieving the described method. The method steps and/or actions may be interchanged with one another without departing from the scope of the claims. In other words, unless a specific order of steps or actions is required for proper operation of the method that is being described, the order and/or use of specific steps and/or actions may be modified without departing from the scope of the claims.

Further, it should be appreciated that modules and/or other appropriate means for performing the methods and techniques described herein, can be downloaded and/or otherwise obtained by a device. For example, a device may be coupled to a server to facilitate the transfer of means for performing the methods described herein. Alternatively, various methods described herein can be provided via a storage means (e.g., random access memory (RAM), read-only memory (ROM), a physical storage medium such as a compact disc (CD) or floppy disk, etc.), such that a device may obtain the various methods upon coupling or providing the storage means to the device.

It is to be understood that the claims are not limited to the precise configuration and components illustrated above. Various modifications, changes and variations may be made in the arrangement, operation and details of the systems, methods, and apparatus described herein without departing from the scope of the claims.

What is claimed is:

1. A method performed by an electronic device, comprising:
generating a depth map of a scene external to a vehicle;
performing first processing in a first direction of the depth map to determine a first non-obstacle estimation of the scene;
performing second processing in a second direction of the depth map to determine a second non-obstacle estimation of the scene;
combining the first non-obstacle estimation and the second non-obstacle estimation to determine a non-obstacle map of the scene, wherein the combining comprises selectively using at least one element selected from the group consisting of a first reliability map of the first processing and a second reliability map of the second processing; and
navigating the vehicle using the non-obstacle map.

2. The method of claim 1, wherein navigating the vehicle comprises providing at least the non-obstacle map as input to an advanced driver assistance systems (ADAS) to regulate at least one of speed or steering of the vehicle.

3. The method of claim 1, wherein the navigating comprises using the non-obstacle map to identify a region of interest that is used by at least one of an object detection algorithm or a lane detection algorithm.

4. The method of claim 1, wherein the vehicle is an autonomous automobile or aerial drone, wherein the navigating comprises navigating the autonomous automobile or aerial drone without human input using the non-obstacle map.

5. The method of claim 1, further comprising generating the depth map using a stereo image pair that is captured by two cameras attached to the vehicle.

6. The method of claim 1, further comprising generating the depth map using a sequence of video images that are captured by a camera attached to the vehicle.

7. The method of claim 1, wherein combining the first non-obstacle estimation and the second non-obstacle estimation further comprises:
performing both the first processing and the second processing in parallel; and
merging the first non-obstacle estimation and the second non-obstacle estimation based on the first reliability map and the second reliability map, wherein a given pixel is identified as a non-obstacle area in the non-obstacle map by comparing a reliability value for the given pixel in the first reliability map and the second reliability map.

8. The method of claim 1, wherein combining the first non-obstacle estimation and the second non-obstacle estimation comprises:
performing first processing of the depth map;
obtaining the first reliability map that includes a reliability value for a plurality of pixels in the first reliability map;
determining reliable regions that include pixels of the first reliability map that have reliability values greater than a threshold;
determining unreliable regions that include pixels of the first reliability map that do not have reliability values greater than the threshold;
identifying the reliable regions of the first reliability map as non-obstacle areas; and
performing second processing on the unreliable regions of the first reliability map to determine whether the unreliable regions are non-obstacle areas.

9. The method of claim 1, further comprising determining the first reliability map, comprising:
determining a segment fitting error for a given segment of pixels in the depth map based on a difference between estimated linear model parameters for the given segment and pre-determined linear model parameters, wherein the pre-determined linear model parameters are selected from among a plurality of road condition models, wherein each of the road condition models has a corresponding set of linear model parameters;
determining a reliability value for the given segment by comparing the segment fitting error to a first estimation threshold; and
applying the reliability value for the given segment to at least one pixel in the given segment.

10. The method of claim 1, further comprising determining the second reliability map, comprising:
determining whether the depth value of a given pixel in the depth map is within a range of a mode of the depth histogram, wherein the given pixel has a high reliability value when the depth value of the given pixel is within the range of the mode of the depth histogram.

11. An electronic device, comprising:
at least one processor;
a memory in communication with the at least one processor; and
instructions stored in the memory, the instructions executable by the at least one processor to:
generate a depth map of a scene external to a vehicle;
perform first processing in a first direction of the depth map to determine a first non-obstacle estimation of the scene;
perform second processing in a second direction of the depth map to determine a second non-obstacle estimation of the scene;
combine the first non-obstacle estimation and the second non-obstacle estimation to determine a non-obstacle map of the scene, wherein the combining comprises selectively using at least one element selected from the group consisting of a first reliability map of the first processing and a second reliability map of the second processing; and
navigate the vehicle using the non-obstacle map.

12. The electronic device of claim 11, wherein the instructions executable by the at least one processor to navigate the vehicle comprise instructions executable by the at least one processor to provide at least the non-obstacle map as input to an advanced driver assistance systems (ADAS) to regulate at least one of speed or steering of the vehicle.

13. The electronic device of claim 11, wherein the instructions executable by the at least one processor to navigate the vehicle comprise instructions executable by the at least one processor to use the non-obstacle map to identify a region of interest that is used by at least one of an object detection algorithm or a lane detection algorithm.

14. The electronic device of claim 11, wherein the vehicle is an autonomous automobile or aerial drone, wherein the instructions executable by the at least one processor to navigate the vehicle comprise instructions executable by the at least one processor to navigate the autonomous automobile or aerial drone without human input using the non-obstacle map.

15. The electronic device of claim 11, further comprising a first camera and a second camera, wherein the first and

second cameras are attached to the vehicle and in communication with the at least one processor, and wherein the instructions executable by the at least one processor to generate the depth map comprise instructions executable by the at least one processor to generate the depth map using a stereo image pair captured by the first and second cameras.

16. The electronic device of claim **11**, further comprising at least one camera attached to the vehicle and in communication with the at least one processor, and wherein the instructions executable by the at least one processor to generate the depth map comprise instructions executable by the at least one processor to generate the depth map using a sequence of video images captured by the at least one camera.

17. The electronic device of claim **11**, wherein the instructions executable by the at least one processor to combine the first non-obstacle estimation and the second non-obstacle estimation further comprises instructions executable by the at least one processor to:

perform both the first processing and the second processing in parallel; and

merge the first non-obstacle estimation and the second non-obstacle estimation based on the first reliability map and the second reliability map, wherein a given pixel is identified as a non-obstacle area in the non-obstacle map by comparing a reliability value for the given pixel in the first reliability map and the second reliability map.

18. The electronic device of claim **11**, wherein the instructions executable by the at least one processor to combine the first non-obstacle estimation and the second non-obstacle estimation comprises instructions executable by the at least one processor to:

perform first processing of the depth map;

obtain the first reliability map that includes a reliability value for a plurality of pixels in the first reliability map;

determine reliable regions that include pixels of the first reliability map that have reliability values greater than a threshold;

determine unreliable regions that include pixels of the first reliability map that do not have reliability values greater than the threshold;

identify the reliable regions of the first reliability map as non-obstacle areas; and

perform second processing on unreliable regions of the first reliability map to determine whether the unreliable regions are non-obstacle areas.

19. The electronic device of claim **11**, further comprising instructions executable by the at least one processor to determine the first reliability map, comprising instructions executable by the at least one processor to:

determine a segment fitting error for a given segment of pixels in the depth map based on a difference between estimated linear model parameters for the given segment and pre-determined linear model parameters, wherein the pre-determined linear model parameters are selected from among a plurality of road condition models, wherein each of the road condition models has a corresponding set of linear model parameters;

determine a reliability value for the given segment by comparing the segment fitting error to a first estimation threshold; and

apply the reliability value for the given segment to at least one pixel in the given segment.

20. The electronic device of claim **11**, further comprising instructions executable by the at least one processor to determine the second reliability map, comprising instructions executable by the at least one processor to:

determine whether the depth value of a given pixel in the depth map is within a range of a mode of the depth histogram, wherein the given pixel has a high reliability value when the depth value of the given pixel is within the range of the mode of the depth histogram.

21. A computer-program product, comprising a non-transitory tangible computer-readable medium having instructions thereon, the instructions comprising:

code for causing an electronic device to generate a depth map of a scene external to a vehicle;

code for causing the electronic device to perform first processing in a first direction of the depth map to determine a first non-obstacle estimation of the scene;

code for causing the electronic device to perform second processing in a second direction of the depth map to determine a second non-obstacle estimation of the scene;

code for causing the electronic device to combine the first non-obstacle estimation and the second non-obstacle estimation to determine a non-obstacle map of the scene, wherein the combining comprises selectively using at least one element selected from the group consisting of a first reliability map of the first processing and a second reliability map of the second processing; and

code for causing the electronic device to navigate the vehicle using the non-obstacle map.

22. The computer-program product of claim **21**, wherein the code for causing the electronic device to navigate the vehicle comprises code for causing the electronic device to provide at least the non-obstacle map as input to an advanced driver assistance systems (ADAS) to regulate at least one of speed or steering of the vehicle.

23. The computer-program product of claim **21**, wherein the code for causing the electronic device to navigate comprises code for causing the electronic device to use the non-obstacle map to identify a region of interest that is used by at least one of an object detection algorithm or a lane detection algorithm.

24. The computer-program product of claim **21**, wherein the vehicle is an autonomous automobile or aerial drone, wherein the code for causing the electronic device to navigate comprises code for causing the electronic device to navigate the autonomous automobile or aerial drone without human input using the non-obstacle map.

25. The computer-program product of claim **21**, further comprising code for causing the electronic device to generate the depth map using a stereo image pair that is captured by two cameras attached to the vehicle.

26. The computer-program product of claim **21**, further comprising code for causing the electronic device to generate the depth map using a sequence of video images that are captured by a camera attached to the vehicle.

27. The computer-program product of claim **21**, wherein the code for causing the electronic device to combine the first non-obstacle estimation and the second non-obstacle estimation further comprises code for causing the electronic device to:

perform both the first processing and the second processing in parallel; and

merge the first non-obstacle estimation and the second non-obstacle estimation based on the first reliability map and the second reliability map, wherein a given pixel is identified as a non-obstacle area in the non-obstacle map by comparing a reliability value for the given pixel in the first reliability map and the second reliability map.

28. The computer-program product of claim **21**, wherein the code for causing the electronic device to combine the first non-obstacle estimation and the second non-obstacle estimation comprises code for causing the electronic device to:

perform first processing of the depth map;

obtain the first reliability map that includes a reliability value for a plurality of pixels in the first reliability map;

determine reliable regions that include pixels of the first reliability map that have reliability values greater than a threshold;

determine unreliable regions that include pixels of the first reliability map that do not have reliability values greater than the threshold;

identify the reliable regions of the first reliability map as non-obstacle areas; and

perform second processing on unreliable regions of the first reliability map to determine whether the unreliable regions are non-obstacle areas.

29. The computer-program product of claim **21**, further comprising code for causing the electronic device to determining the first reliability map, comprising code for causing the electronic device to:

determine a segment fitting error for a given segment of pixels in the depth map based on a difference between estimated linear model parameters for the given segment and pre-determined linear model parameters, wherein the pre-determined linear model parameters are selected from among a plurality of road condition models, wherein each of the road condition models has a corresponding set of linear model parameters;

determine a reliability value for the given segment by comparing the segment fitting error to a first estimation threshold; and

apply the reliability value for the given segment to at least one pixel in the given segment.

30. The computer-program product of claim **21**, further comprising code for causing the electronic device to determine the second reliability map, comprising code for causing the electronic device to:

determine whether the depth value of a given pixel in the depth map is within a range of a mode of the depth histogram, wherein the given pixel has a high reliability value when the depth value of the given pixel is within the range of the mode of the depth histogram.

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